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The Project Success of IT Outsourcing Vendors – The Influence of IT Human Resource Management and of the Governance Structure

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Preface

This dissertation is the end result of a process that started during my master program "Finance and Information Management". As this program was quite research focused, it included a three-month guided research phase. Dr. Markus Böhm was my supervisor and supported me in writing my first paper. This paper developed a carve-out maturity model and was presented at the Wirtschaftsinformatik 2015 conference. The guided research phase arouse my interest in the world of research. During writing my master thesis, I was convinced by my supervisor Prof. Dr. Michael Schermann to apply for a position at the Chair for Information Systems of Prof. Dr. Helmut Krcmar. I joined the research team of Dr. Manuel Wiesche in January 2015 together with Maximilian Schreieck, whom I already knew well from our time at TUM: Junge Akademie. Now, over four years later, I do not regret the decision at all to first have a look into the world of research and then pursue a career in industry.

I like to thank my supporters. This dissertation would not have been possible without their help. First of all, special thanks to my doctoral advisor Prof. Dr. Helmut Krcmar for the possibility to be part of his chair and for all the opportunities that he has offered me. I had the great opportunity to visit Prof. Damien Joseph in Singapore for six weeks and to visit all conferences where my papers had been accepted. I also like to thank his wife Carol Krcmar for her great help in improving the language and the readability of my papers. I am deeply indebted to my research group manager Dr. Manuel Wiesche. Despite his tight schedule, he always took his time for discussions and giving advice. Manuel's demanding but also rewarding management style helped my dissertation project to always remain on track. I also owe thanks to my colleague Maximilian Schreieck. His structured and organized way of working helped us a lot in finishing our research project ExCELL. Furthermore, I like to thanks my colleagues Michael Lang, Tobias Riasanow, Jörg Weking, Thomas Köhn and Dr. Harald Kienegger for their friendship inside as well as outside of the office.

Special thanks also to my parents. Their support throughout my life and the values that they have taught me lay the foundations for this dissertation. Last, but not least, many thanks to my girlfriend Laura for her understanding and encouragement. She was a great support during the final months of this dissertation.

Munich, April 2019 Christoph Pflügler

Abstract

This cumulative dissertation analyzes the influence of human resource management and of project governance on the project success of IT outsourcing vendors. Within this broad research area, I consider the following three research areas. First, the formation of subgroups within IT project teams and their influence on project performance are analyzed. Second, I consider the influence of shock events on the turnover of IT professionals and possible retention strategies to prevent turnover. Third, factors influencing the choice of project governance that should be part of an endogenous theory of IT outsourcing are analyzed. These research areas are analyzed with a mixed-method approach, but most studies have a quantitative approach due to the access to a unique archive data set of a German IT outsourcing vendor. In total, this cumulative dissertation comprises seven publications that address these three research areas. Regarding subgroups in IT project teams, we find that identity-based factors do not lead to the formation of subgroups. However, geographical distance, language, previous ties, and task assignment based subgroups emerge in IT teams. Our results show that subgroups have a positive as well as negative influence on project performance depending on the subgroup type. Regarding the second research area, we find that turnover spreads in the organizational network of IT organizations. Our findings suggest that retention strategies have to be aligned with the characteristics of the respective IT professional. Regarding the choice of project governance, we find that environmental uncertainty is the only construct of transaction cost economics with a high influence on the choice of project governance, and that an endogenous theory of IT outsourcing should consider a multi-level approach. The obtained findings are subject to limitations. First, most of the studies are based on a large archive data set that comes from only one IT outsourcing vendor, which limits the generalizability of our findings. Second, the data quality of single attributes of the data set is low. Third, the operationalization of constructs as specified by the original theory was sometimes quite challenging. Fourth, certain models only show moderate explanatory power. Fifth, the data set only contains data that is observable by the IT outsourcing vendor and no psychological data of the employees. This dissertation discusses possibilities for future research regarding the three research areas and regarding other research areas that can be addressed by the unique archive data set.

Table of Contents

List of Figures

List of Tables

List of Appendices

List of Abbreviations

ACM	Association for Computing Machinery
AIS	Association for Information Systems
AMCIS	Americas Conference on Information Systems
AOM	Academy of Management
CON	Conference
CPR	Computers and People Research
e.g.	Exempli Gratia
GAM	General Additive Models
H	Hypothesis
HHI	Herfindahl-Hirschman-Index
HICSS	Hawaii International Conference on System Sciences
ICIS	International Conference on Information Systems
IRWITPM	International Research Workshop on Information Technology Project Management
IS	Information Systems
IT	Information Technology
ITO	Information Technology Outsourcing
JNL	Journal
JSIS	The Journal of Strategic Information Systems
MISQ	Management Information Systems Quarterly
MISQE	Management Information Systems Quarterly Executive
NLSY	National Longitudinal Survey of the Youth
NR	Not Ranked
P	Publication
RQ	Research Question
SIGMIS	Special Interest Group on Management and Information Systems
SOEP	Socio-Economic Panel
TCE	Transaction Cost Economics
VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.

Part A

1. Introduction

1.1 Motivation

Most of the research on the success of information technology outsourcing (ITO) has focused on the customer side and has disregarded the other side, namely the business performance of the ITO vendor. According to a literature review of Lacity, Khan, Yan, and Willcocks (2010), only 8 of 741 analyses considered ITO vendor's business performance as the dependent variable. However, the competition in the ITO market has increased in recent years (Manning, Lewin, & Schuerch, 2011). Therefore, ITO vendors have to understand how to conduct successful projects and stay profitable. The profitability of ITO projects is influenced by many factors, among them the chosen project governance mechanism and the management of human resources (Faraj & Sproull, 2000; Gopal & Sivaramakrishnan, 2008; Huckman, Staats, & Upton, 2009).

The dynamics within the team can have a great influence on the performance of the project (Mitchell et al., 2015). One important aspect of team dynamics are subgroups within the project team (Carton & Cummings, 2012), as they for instance influence the way the team members communicate with each other and share their knowledge. However, it remains unclear how subgroups emerge in IT project teams and how they influence performance.

Another human resource management related factor that has an influence on the project performance is turnover (Gopal & Koka, 2012). In addition to the negative influence on the current project, turnover is also problematic for the vendor in general. First, it is difficult to find a replacement due to the high demand in the IT labor market (Streim & Pfisterer, 2014; Torpey, 2016). Second, turnover creates high costs through recruiting and training, but also through the disruption of organizational processes (Chang, 2010; Sumner & Niederman, 2004; Thatcher, Stepina, & Boyle, 2002). Turnover and the retention of IT professionals is always among the most important issues of IT managers (Kappelman et al., 2018). However, it is unclear which retention strategy should be taken by IT managers, as IT professionals have different characteristics. Several different turnover theories exist, among them the unfolding model of turnover that argues that shock events trigger the turnover of employees (Lee & Mitchell, 1994). However, it remains unclear how shock events influence the turnover of IT professionals, which has also been pointed out by Joseph, Ng, Koh, and Ang (2007).

The performance of ITO projects is influenced by the chosen project governance that is predominantly determined by the contract type (Gopal & Sivaramakrishnan, 2008; Gopal, Sivaramakrishnan, Krishnan, & Mukhopadhyay, 2003; Schermann, Dongus, Yetton, & Krcmar, 2016). Transaction cost economics (TCE) has been the dominant theoretical framework for analyzing the chosen governance mechanism for ITO projects (Dibbern, Goles, Hirschheim, & Jayatilaka, 2004; Klein, 2002). However, there is an ongoing discussion on its applicability in the ITO domain (Karimi-Alaghehband, Rivard, Wu, & Goyette, 2011; Lacity, Willcocks, & Khan, 2011; Schermann et al., 2016). Lacity et al. (2011) and Schermann et al. (2016) call for the development of a new endogenous theory for analyzing ITO to address the empirical shortcomings. However, it is not clear which constructs should be part of this new theory and how it could be structured.

To address the previously mentioned points, additional research on IT human resource management, project governance and their influence on the project success of ITO vendors should be conducted. This cumulative dissertation addresses them with a mixed-method approach. However, most of the conducted studies have a quantitative approach because of the access to a unique quantitative data set from a leading German ITO vendor, called ALPHA due to confidentiality reasons. The data set covers more than 36,000 projects and information on more than 8.000 involved IT professionals. It is described in detail in section 4.1 of part A of this dissertation.

In total, this cumulative dissertation comprises seven publications. We find that identity-based factors do not lead to the formation of subgroups, which is in contrast to findings in other domains. Subgroups based on geographical distance and language emerge in all IT project teams. Previous ties are influential only in agile projects whereas task assignment only in traditional projects. Whether subgroups have a positive or negative influence on project performance depends on the type. For instance, subgroups based on team familiarity have a positive influence, whereas subgroups based on task familiarity tend to have a negative influence.

We find that turnover spreads within IT organizations; not only among current team members, but also former team members and indirect contacts within the organization seem to be influenced by the turnover of co-workers. Furthermore, our results show that strategies to retain an IT professional have to be aligned with the characteristics of the respective IT professional, like current stage of his career, the motivations for working for the current employer, his relationships with co-workers or the current job situation.

We find that environmental uncertainty is the only TCE construct with a high influence on the choice of project governance. The other constructs only show limited influence. However, we find that previous contract on the client level and industry IT intensity on the industry level are highly influential. Therefore, a multi-level approach should be considered by an endogenous theory of ITO. Additionally, we find that the danger of opportunistic behavior, which is a central assumption of the TCE theory, has decreased in the ITO market over the time.

The obtained findings are subject to limitations. First, most of the studies are based on a large archive data set that comes from only one ITO vendor, which limits the generalizability. Second, the data quality of a single attributes of the data set is low. Third, the operationalization of constructs as specified by the original theory was sometimes quite challenging. Fourth, certain models only show moderate explanatory power. Fifth, the data set only contains data that is observable by the ITO vendor and no psychological data of the employees.

In addition to future research possibilities based on the unique data set, this dissertation opens up several possibilities for research on subgroups within IT project teams, on the turnover of IT professionals and on the choice of governance for ITO projects.

1.2 Structure

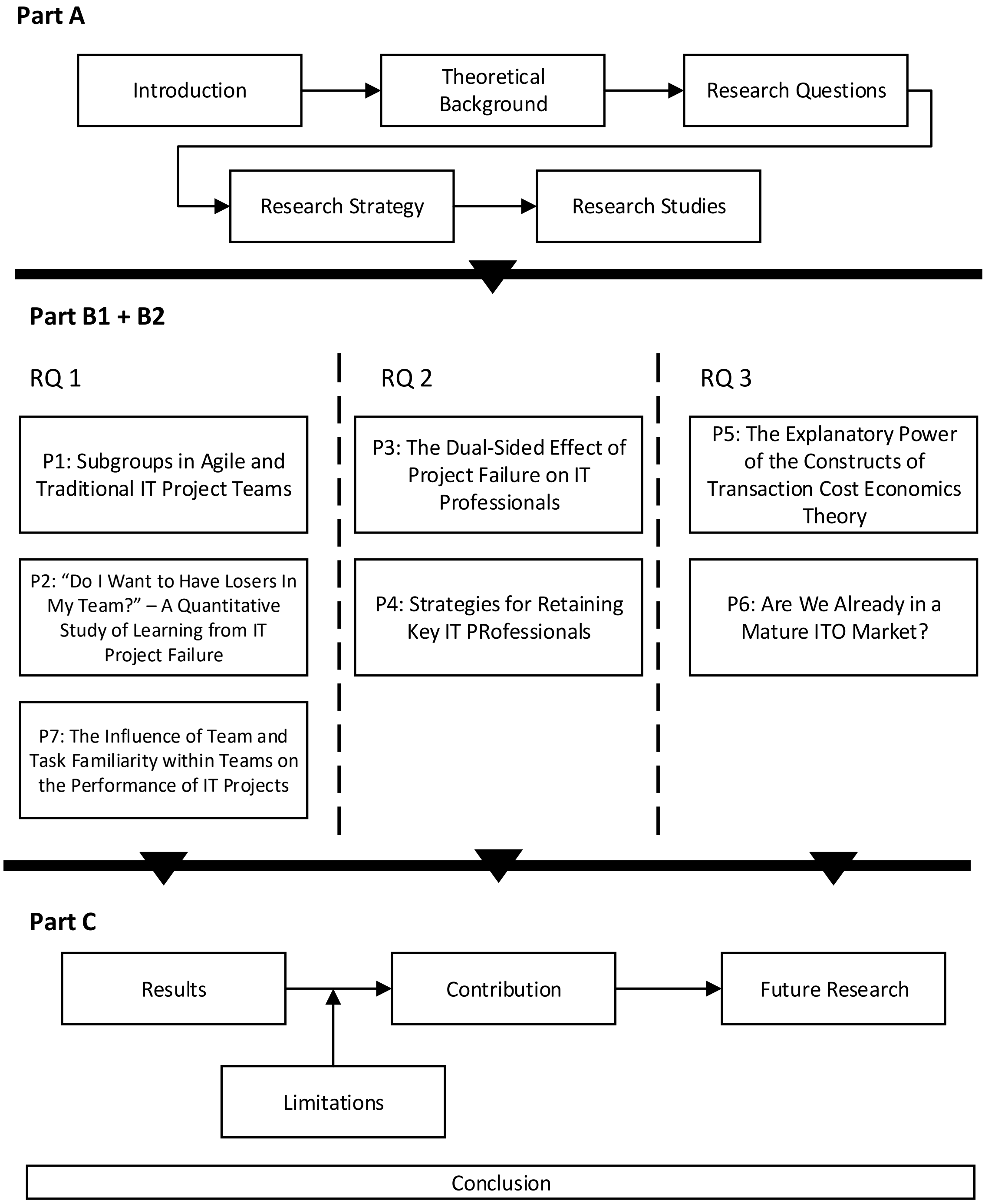

Figure 1. Thesis Structure

This thesis is structured into three main parts. The first part (Part A) starts with a brief introduction of the topics covered in this thesis. The next section outlines the theoretical background, namely the project performance of ITO vendors, the human resource management in IT projects and the choice of governance for ITO projects. Next, the research questions addressed by this thesis are described. Then the research strategy, including the employed data set and the research approach are presented. Part A ends with a short description of the research studies of this thesis.

The second part (Part B) presents the conducted research studies that address the three research questions of this thesis. The research questions are analyzed in three different research areas.

The third part (Part C) starts with a summary of the results of the conducted research studies. Before the contributions to theory and practice, limitations of this thesis are mentioned. Then, possibilities and directions for future research are outlined. This thesis ends with a short conclusion.

2. Theoretical Background

This chapter describes previous research project performance of ITO vendors, the human resource management in IT projects and the governance of ITO projects that form the theoretical basis of this dissertation.

2.1 Project Performance of ITO Vendors

Outsourcing is a combination of the terms “outside”, “resource” and “using” (Krcmar, 2015). IT outsourcing is defined as the assignment of an IT task to an ITO vendor, who charges a fee for conducting the service (Apte et al., 1997; Krcmar, 2015; Lacity & Hirschheim, 1993). These IT tasks can be various and range from “simple data entry to software development and maintenance, data center operations and full system integration” (Apte et al., 1997, p. 289). The employed definition of ITO considers any IT task that is performed by a third party.

Lacity et al. (2010) reviewed literature on empirical ITO studies. According to their results, only 8 of 741 empirical studies considered the ITO vendor’s business performance as the dependent variable. The business performance is mostly dependent on the performance of the conducted projects, as they are the main way of generating revenue by ITO vendors. In previous research several measures, such as the project profitability (Gopal & Koka, 2010; Hoermann, Hlavka, Schermann, & Krcmar, 2015; Schermann, Lang, Hörmann, Swanson, & Krcmar, 2014), the absolute profits (Ethiraj, Kale, Krishnan, & Singh, 2005; Gopal & Koka, 2012; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003) and the project price (Gefen, Wyss, & Lichtenstein, 2008) have been employed as a proxy for project performance.

The project performance of ITO vendors is a complex construct that is influenced by many different factors. Factors that have been analyzed are e.g. project duration, project size, customer experience and team size (Banerjee & Duflo, 2000; Chen & Bharadwaj, 2009; Ethiraj et al., 2005; Gopal & Koka, 2010, 2012; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003; Hoermann et al., 2015; Mani, Barua, & Whinston, 2013; Schermann et al., 2014). But also other factors like the governance of the project (Ethiraj et al., 2005; Gopal et al., 2003; Hoermann et al., 2015) or the turnover within the project team (Gopal & Koka, 2012; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003) have been analyzed.

The recent years in the ITO market are characterized by a commoditization of ITO services (Lacity & Willcocks, 2014; Manning et al., 2011). ITO has become a routine part of management and is not an exception anymore (Lacity et al., 2010). Additionally, ITO clients became more familiar with the selection of the vendor (Manning et al., 2011). A reason for this could be that they already had several outsourcing relationships and learned from their mistakes (Lacity et al., 2010). The availability of alternative ITO vendors is as well growing (Gonzalez, Gasco, & Llopis, 2006), which makes it easy for customers to switch (Lewin & Couto, 2007). Nowadays, ITO vendors not only consider their home market, but actively pursue a global strategy and compete on six continents (Lacity et al., 2010). Because of these reasons, there is high competition in the ITO market (Manning et al., 2011). As a reaction, ITO vendors became more specialized and developed their capabilities during the last years (Lacity, Khan, & Willcocks, 2009).

2.2 Human Resource Management in IT Projects

Topic	Sample Research Questions
Definition	• Who is an IT professional? • How do IT professionals act as knowledge brokers in organizations? • What are the key skills and knowledge requirements of IS professionals?
Careers in IT	• Does the dichotomy of career paths – technical versus managerial – still hold for IT professionals? • What are the dynamic career orientations of IT professionals?
Compensation	• What is the impact of human capital on compensation earned by IT professionals? • Do incumbent employees receive corresponding increases in compensation for their tenure at a particular organization? • Do MBA education and IT experience provide value for IT professionals?
Training and Outsourced IT service providers	• What is the impact of training on employee performance in IT outsourcing firms? • What is the impact of employee training on firm performance in IT outsourcing firms? • Which indicators of ability (technical or functional) are relatively more important for vendors who provide software services through e-markets?
Innovation and R&D	• Does employee education lead to higher R&D productivity in IT firms? • What is the role of ability in individuals' decision to become entrepreneur's vis-à-vis scientists in the IT industry?
Gender	• How do factors in the workplace affect the experience of women IT professionals? • What is the impact of Millennials' intense interaction with IT on gender stereotypes in the IT workforce? • Will women receive lower salaries than men, even when controlling for other human capital factors that may explain the salary inequities?
IT staffing	• How do IT leaders' view the current and emerging market for IT professionals? • What HR practices are followed by industry leaders to meet the challenges in IT labor markets posed by rapidly changing technology and transformation of IT function in organizations? • How do firms ensure that IT professionals have skills needed to compete in an environment of technical and business uncertainty? • What factors motivate different levels of IT managers?
Turnover and Burnout	• What is the impact of turnover on internal labor market in IT firms? • What factors determine the turnover intentions of IT professionals? • What is the role of exhaustion in turnover intentions of IT professionals? • What are the different routes through which IT professionals leave current employment?
HR Strategies	• What is the right HR strategy for managing IT professionals? • How can IT leaders develop a workforce that is capable of fulfilling a strategic role?

Table 1: Classification of IT research on human resource management according to Ang, Banker, Bapna, Slaughter, and Wattal (2011)

As IT is a knowledge intense area, people are an integral part of development, maintenance and management of IT (Ang et al., 2011). Research on human resource management in IT can be grouped into the categories shown in Table 1 (Ang et al., 2011).

Human Resource Management is different in IT than in other domains, because IT work is different. IT Professionals have an own organizational culture (Guzman, Stam, & Stanton, 2008). This is due to various reasons. For example, in comparison to some other professions, IT work is conducted mostly in teams (Tang & Kishore, 2010). These teams are not stable over time, but are formed for completing certain tasks and then disband after the project has been finished (Huckman & Staats, 2011; Huckman et al., 2009; Niederman, 2016). These teams are called fluid teams. Due to this, IT professionals work together with many different other IT professionals and build a large social professional network.

Another characteristic of IT professionals and IT teams is that expertise in IT teams is distributed among different members (Kudaravalli, Faraj, & Johnson, 2017). Expertise can be related to different aspects, like the employed technologies or methodological competences. This decentrality of knowledge in IT projects influences the way of collaboration within the project.

IT professionals work together closely in the project and exchange themselves intensively (Madsen & Matook, 2010; Vidgen & Wang, 2009). This exchange has intensified in recent years due to agile project management, which has gained popularity in recent years (Brhel et al., 2015). Due to agile procedures like daily stand-up or pair programming, there are close and informal exchanges between the team members.

The motivation of IT professionals is different in comparison to other professions. For instance, the motivation to work for a certain organization can be divided into three groups: extrinsic motivation, intrinsic motivation and social motivation (Venkatesh, Windeler, Bartol, & Williamson, 2017). For instance, the intrinsic motivation is different. IT knowledge loses its significance due to the dynamic of IT. It is estimated that the half-life of IT knowledge is less than two years (Ang & Slaughter, 2000). Because of this, IT professionals can be motivated by offering trainings. Another special circumstance in IT is the altruistic motivation of IT professionals to engage in open source projects (Mehra, Dewan, & Freimer, 2011).

Another characteristic of IT work is the presence of a high project failure rate. According to The Standish Group (2013), the failure rate of IT projects is higher than 60% and it has not significantly decreased in recent years. Although this figure seems to be estimated rather high, it shows the problem. IT professionals often face the circumstance to cope with failures.

In comparison to other professions, IT work can be conducted virtually (Sarker & Sahay, 2003). This makes virtual collaboration in teams possible. However, virtual teams influence the team collaboration, as e.g. informal exchange between team members is difficult. Another aspect is that virtual team often span different time zones and different cultures, which also have an influence on the collaboration within the team (Sarker & Sahay, 2004).

Careers in the IT profession are characterized by a high rate of professionals leaving the IT domain (Joseph et al., 2007). Another characteristic is the high demand of IT professionals in the market in comparison to other professions (Dishman, 2015; Torpey, 2016). Therefore, IT professionals have the ability to easily find a new job in another organization.

Another characteristic of IT work is the underrepresentation of females in the IT workforce (Trauth, 2013). This underrepresentation might influence several aspects, like the formation of subgroups as gender has been found to be a factoring causing subgroup formation in other domains (Lau & Murnighan, 1998).

These reasons make human resource management specific in the IT domain. As IT work is conducted in form of projects, IT professionals are also an important part of IT projects (Tang & Kishore, 2010; Vidgen & Wang, 2009). In the following, two aspects of human resource management in IT projects, the turnover of IT professionals and subgroups within IT project teams, are discussed in more detail.

2.2.1 Turnover of IT Professionals

Turnover is defined as "voluntarily leaving an IT job for an alternative IT job with a different employer" (Joseph, Ang, & Slaughter, 2015). Turnover of professionals is a common phenomenon in the IT industry. According to survey among Fortune 500 companies, IT companies experience much higher turnover rates than other companies (Dishman, 2015). Turnover is problematic for IT organizations mainly due to two reasons.

First, finding a successor to someone who has quit is often difficult due to the high demand for skilled IT professionals in the global IT labor market (Streim & Pfisterer, 2014; Thibodeau, 2012). Programming is one of the most sought after professions (Torpey, 2016). Moreover, high demand for skilled and specialized IT professionals is predicted to continue to increase in the future (Strauss, 2017).

Second, turnover creates high costs for IT organizations through recruiting and training (Chang, 2010; Sumner & Niederman, 2004; Thatcher et al., 2002). Studies estimate these costs to be between 90% and 700% of the annual salary of an IT professional (Allen, Bryant, & Vardaman, 2010; Kochanski & Ledford, 2001). One reason for such high costs is the time it takes for a new IT professional to become fully productive, which one study estimated to be around 18 months (Baroudi, 1985).

Turnover is not only problematic on the organizational level, but also on the project level. If an IT professional leaves, the processes within the project are interrupted (Thatcher et al., 2002). Due to this, the performance of the project is influenced, if one of the team members commits turnover (Abdel-Hamid, 1992; Gopal & Koka, 2012). Furthermore, studies have shown that high turnover rates can increase the costs and duration of projects by up to 60 percent (Abdel-Hamid, 1989). Turnover also affects the remaining team members by causing employee-related problems such as poor job attitudes (Abdel-Hamid, 1989; Dess & Shaw, 2001; Pennings, Lee, & Van Witteloostuijn, 1998; Zylka & Fischbach, 2017).

IS research has identified more than 43 conceptually distinct antecedents of IT turnover (Ghapanchi & Aurum, 2011; Joseph et al., 2007). Some of the more researched factors preceding turnover are job satisfaction, task-based characteristics, affective commitment, age, gender, organizational tenure or role conflict (Joseph et al., 2007). Empirical studies suggest that a combination of different antecedents add up to what is considered an individual's point of no return: the threshold that actually causes turnover behavior (Josefek & Kauffman, 2003; Niederman, Sumner, Maertz, & Carl, 2007).

Various theories exist for explaining the turnover of individual IT professionals (Joseph et al., 2007):

1. *Organizational Equilibrium Theory*: This theory goes back to March and Simon (1958). According to this theory, professionals leave an organization, if they perceive that their contribution to the organization is larger than the motivation to work for the organization. This is mainly influenced by two factors: (1) one's satisfaction with the work environment, and (2) one's ease of movement. Many other theories on turnover build on aspects of the organizational equilibrium theory.

2. *Met Expectations Theory*: Based on the organizational equilibrium theory, this theory argues that met expectations are a key issue in turnover decisions (Porter & Steers, 1973). Met expectation is defined as "the discrepancy between what a person encounters on the job in the way positive and negative experiences and what he expected to encounter" (Porter & Steers, 1973). Expectations of a professional might be related to rewards, advancement and relations with co-workers.
3. *Linkage Model*: This theory goes back to Mobley (1977) and argues that there is a series of intermediate linkages between job satisfaction and turnover. Job dissatisfaction triggers job search behavior which develops into turnover intention when other appropriate jobs are available on the job market.
4. *Unfolding Model of Voluntary Turnover*: This turnover theory is based on the work of Lee and Mitchell (1994). According to this theory, professionals follow one out of four psychological paths before committing turnover. These paths are often triggered by a shock event. Niederman et al. (2007) analyze which psychological paths are taken by IT professionals. The results show that they have own specific paths and that turnover behavior of IT professionals is different than in other domains.
5. *Job Embeddedness Theory*: According to this theory, some professionals do not commit turnover because they are strongly embedded due to the current job (Mitchell & Lee, 2001) Job embeddedness consists of the embeddedness within the organization, but also of the embeddedness within the community. Within these two areas of embeddedness, there are links to other people or specific tasks, fit to certain aspects of the community and organizations, as well as things that have to be sacrificed when leaving that determine the embedded of an individual.

In order to prevent the turnover of an IT professional, different retention actions have been proposed. They can be grouped in the following five categories:

1. *Financial or Non-financial Compensation*: Financial compensation, such as a pay raise or a bonus, is likely to increase job satisfaction and may be perceived as a form of appreciation (Agarwal, Brown, Ferratt, & Moore, 2006; Joseph et al., 2015). Non-financial compensation, such as motivational feedback or team building events, also influence retention (Agarwal & Ferratt, 1998) and can be a cost-effective way of retaining employees. Fortunately, this type of compensation requires minimal effort to implement on the part of the IT manager.
2. *Working Arrangements*: Special working arrangements may help to retain an IT employee (Agarwal & Ferratt, 1998; Niederman et al., 2007). These arrangements include office workspace, the work location of the employee, the possibility of working from home and flexible working hours (Agarwal & Ferratt, 1998).
3. *Career Development Opportunities*: Career development is an important issue for many IT professionals. Promotion is an obvious way to advance an IT employee's career (Agarwal & Ferratt, 1998), but providing training can be used to achieve the same end (Agarwal et al., 2006).
4. *Change of Department*: Relationships with co-workers and supervisors can influence retention rates (Agarwal et al., 2006; Agarwal & Ferratt, 1998). If these relationships are poor or unsatisfactory, assigning an IT employee to a different department within the IT organization with a different supervisor can provide the employee with the opportunity to make a fresh start.

5. *Varying Work Tasks*: Performing the same or similar tasks repetitively over an extended period can lead to boredom and possibly hinder an IT employee from reaching his or her full potential. Providing an opportunity to work on a new and challenging task can be motivating (Niederman et al., 2007).

2.2.2 Subgroups in IT Projects

Subgroups within a project team are triggered by dividing lines, so called faultlines, that are based on attributes of diversity of team members (e.g. age, gender, knowledge or values) (Bezrukova, Jehn, Zanutto, & Thatcher, 2009; Carton & Cummings, 2012; Gibson & Vermeulen, 2003; Lau & Murnighan, 1998, 2005). A subgroup is a subset of team members that is characterized by the unique form of a certain attribute (Carton & Cummings, 2012). Whether subgroups emerge depends on the intensity of the division by the faultline (Carton & Cummings, 2013). For instance, the division between team members with an age of 40 and 50 might not be as intense as the division between members that are 20 and 50 years old.

As all team members have a common goal, different subgroups have to interact and rely on each other (Carton & Cummings, 2012). Because of this, the team performance is influenced by the existence of different subgroups within a project team (Carton & Cummings, 2013; Gibson & Vermeulen, 2003; Lau & Murnighan, 2005; Mitchell et al., 2015). In literature, several reasons for the influence of subgroups on team performance are mentioned. The majority argues that they have negative influences. In the case subgroups exists within the team, trust differs between the different subgroups. Furthermore, most of the interactions occur within the subgroup and as a result knowledge about the expertise of others only develops within the same (Ellis et al., 2003; Kane, Argote, & Levine, 2005). Due to the imbalance of interactions between the team members, knowledge sharing is impaired as well (Privman, Hiltz, & Wang, 2013). However, subgroups might also have positive influences. As they divide large teams into smaller units with fewer members, trust between individual members develops faster (Amason, 1996). Furthermore subgroups give a team a certain structure, which has been found to have a positive influence on project performance (Bunderson & Boumgarden, 2010).

Literature distinguishes three types of subgroups (Carton & Cummings, 2012).

1. *Identity-based subgroups*: Members of this type of subgroup are characterized by the same identity characters like e.g. personal values, gender or age (Hogg & Terry, 2000).
2. *Knowledge-based subgroups*: They are formed based on factors like e.g. technical language (Homan, Van Knippenberg, Van Kleef, & De Dreu, 2007). Members of this type of subgroup poses a similar type of knowledge. They often share information or use this form of exchange to solve problems and tasks together (Carton & Cummings, 2012).
3. *Resource-based subgroups*: They are based on the idea of group conflict theory (Esses, Jackson, & Armstrong, 1998) as well as on theories of inequality and organizational ranks (Blau, 1977). Members of this type of subgroup differentiate according to the ability to claim resources, such as decision power (Carton & Cummings, 2012). Resource-based subgroups often form based on the hierarchical level.

2.3 Governance of IT Outsourcing Projects

The Governance of ITO projects influences the performance of a project (Ethiraj et al., 2005; Gopal et al., 2003; Hoermann et al., 2015). It is mostly determined by the contract type. There are two basic types of ITO contracts: fixed price (FP) and time & material (TM) (Banerjee & Duflo, 2000; Wieczorrek & Mertens, 2011). In FP contracts, the ITO vendor agrees to deliver a predefined result and gets compensated with a certain fee (Ethiraj et al., 2005; Wieczorrek & Mertens, 2011). TM contracts are different, because the billing is based on the agreed hourly rate and the working hours that the ITO vendor invested (Ethiraj et al., 2005; Wieczorrek & Mertens, 2011). In practice, there are also hybrid forms between FP and TM contracts. The choice of contract is more like a continuum than a black-and-white decision. One such form is that different phases of the project have different types of contract (Banerjee & Duflo, 2000) or another form is that the contract basically is a TM contract, but with a cap that limits the number of hours that the ITO vendor can bill (Kalnins & Mayer, 2004). These hybrid forms are normally not considered in this dissertation in order to focus on the two extremes of the continuum.

The choice between the two contract types depends on various factors, such as the certainty of the requirements (Banerjee & Duflo, 2000; Gopal et al., 2003; Kalnins & Mayer, 2004), on the risk of employee attrition (Gopal & Sivaramakrishnan, 2008), on the reputation of the ITO vendor (Banerjee & Duflo, 2000), on the business familiarity (Gefen et al., 2008) and on the amount of risk each party has to bear (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003; Lacity & Hirschheim, 1993). The ITO vendor has to bear most of the risk in FP contracts and therefore he should be compensated with higher project profitability. However, empirical results do not support this claim (Ethiraj et al., 2005; Gopal et al., 2003). An explanation for this could be that the client has more bargaining power and therefore the ITO vendor does not get his preferred contract choice (Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003).

Transaction cost economics (TCE) is the preferred theoretical framework for explaining the choice of contract in ITO literature. TCE goes back to Williamson (1979) and Williamson (1985). It is based on two behavioral assumptions regarding the involved actors (Karimi-Alaghehband et al., 2011):

1. *Bounded rationality*: The involved actors try to behave rational, but they are bounded by their mental capacity (Williamson, 1985).
2. *Opportunism*: The involved actors pursue their self-interest with guile (Williamson, 1985).

Three central constructs of TCE are uncertainty, transaction frequency and asset specificity (Williamson, 1985).

1. *Uncertainty*: It can be divided into environmental and behavioral uncertainty (Williamson, 1985). Environmental uncertainty is related to uncertainty that stems from the lack of knowledge about the future state regarding the transaction environment (Susarla, Barua, & Whinston, 2009). Behavioral uncertainty deals with uncertainty that originates from the lack of knowledge regarding the actions of the in the transaction involved actors (Susarla et al., 2009).

2. *Asset specificity*: It is defined as the "degree to which the assets used to conduct an activity can be redeployed to alternative uses and by alternative users without sacrifice of productive value" (Williamson, 1996). It can be divided into site specificity (geographical site of investment), physical asset specificity (Equipment and tools) and human asset specificity (knowledge and learning of employees) (Karimi-Alaghehband et al., 2011).
3. *Transaction frequency*: It focuses on the recurrence of activities that are needed for the transaction (Karimi-Alaghehband et al., 2011). Transactions can occur only occasionally, but also permanently.

Recently, the role of TCE in ITO research has been criticized. Two major reviews (Karimi-Alaghehband et al., 2011; Lacity et al., 2011) and a meta-analytic review of the choice of contract form in ITO (Schermann et al., 2016) report results that are inconsistent with TCE theory. Karimi-Alaghehband et al. (2011) report that only a few studies either operationalize TCE constructs rigorously or include all of the TCE constructs. They suggest a more rigorous application of TCE in ITO research to resolve the inconsistencies. In contrast, Lacity et al. (2011) argue that the results rise doubts about the applicability of TCE in the ITO domain. They call for the development of an endogenous theory of ITO. Schermann et al. (2016) focus on the effects of uncertainty on contract choice. They report two findings. First, operationalization of uncertainty has a significant effect on contract choice, which supports the call by Karimi-Alaghehband et al. (2011) for a more rigorous application of TCE. Second, the strength of this effect has declined over time, becoming non-significant for ITO projects that begun in 2000 or later. This finding supports the call by Lacity et al. (2011) to develop a new endogenous theory of ITO.

3. Research Questions

The dissertation is structured by three research questions (RQ), which are outlined in the following section. The main overall dependent variable is project success. The three research questions consider constructs that either directly or indirectly influence project success. Figure 2 shows the relationship between the research questions. This dissertation is heavily based on a large archive data set that is described in detail in section 4.1. This data set was especially suitable for analyzing the chosen research questions.

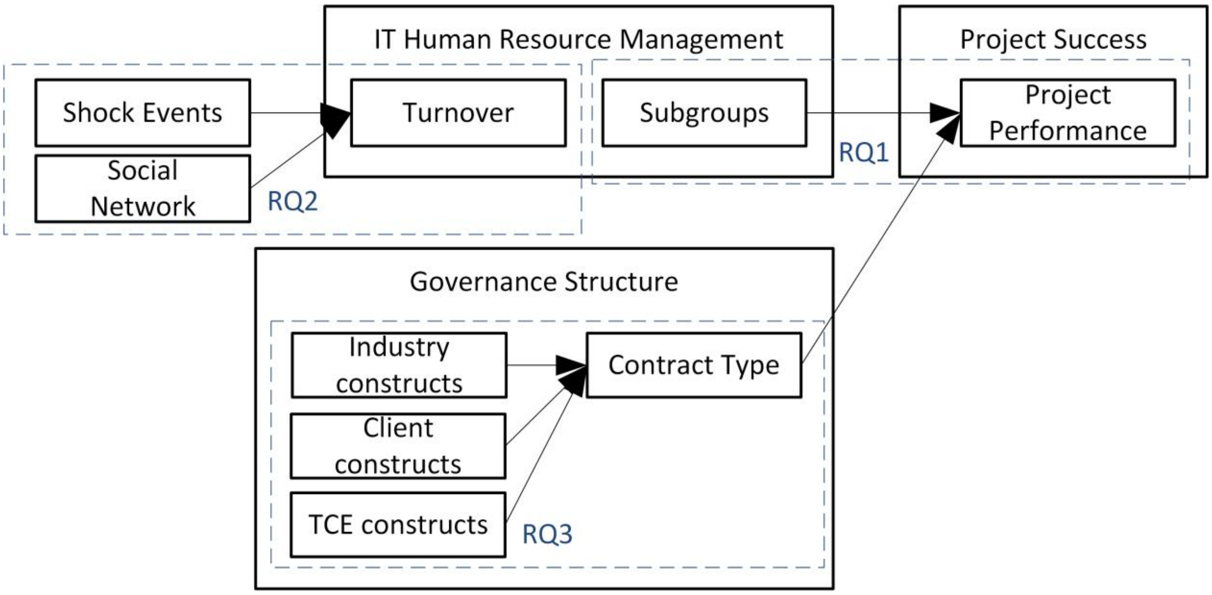

Figure 2. Structure of Research Questions

RQ1: "How do subgroups form and what is their influence on the performance of ITO projects?"

The first research question considers the relationship between IT human resource management and project success and focuses on subgroups within IT project teams. Many different factors that lead to the formation of subgroups has been analyzed in general management literature, e.g. demographic factors (Lau & Murnighan, 1998), language and cultural (Dau, 2016; Hinds, Neeley, & Cramton, 2014; Lau & Murnighan, 1998) or knowledge (Carton & Cummings, 2012). However, these factors have not yet been analyzed in IT teams. They might have a different effect due to the characteristics of IT work. In addition, there are IT specific context factors that might influence or lead to the formation of subgroups.

In addition to the formation of subgroups within IT project teams, the influence of subgroups on project performance is analyzed. As previously mentioned, subgroups can have a positive as well as negative influence on project performance. The influence of two IT specific subgroups are analyzed in this research question. First, subgroups based on task familiarity and team familiarity are considered. As IT projects are normally conducted by fluid teams formed for a designated, temporary period of time, some of the team members might have worked together in the past while others do not know each other at all (Huckman & Staats, 2011; Huckman et al., 2009). Not only team familiarity is special within IT, but also task familiarity. IT professionals have to conduct a diverse range of tasks during a project (Huckman & Staats, 2011). They might have already conducted some of these tasks in the past while others are unknown. Second, subgroups based on team members that have experienced a project failure in the past are considered. This type of subgroup is specific for the IT domain as project failures are quite common (The Standish Group, 2013).

RQ2: "Is turnover influenced by external events and retention strategies?"

The second research question considers the turnover of IT professionals, which is another factor that influences project success. Previous research has found that it has a negative relationship with project performance (Gopal & Koka, 2012; Gopal & Sivaramakrishnan, 2008). It would have been possible to try to reproduce this relationship based on the archive data set, but a more relevant question is which factors influence turnover and how can it be prevented.

As previously outlined, several theories for explaining turnover exist, among them the unfolding model of voluntary turnover after Lee and Mitchell (1994), which has gotten more popular in recent turnover research (Allen, Hancock, Vardaman, & McKee, 2014). It focuses on the decision process of turnover and argues that a shock event often acts as a trigger. Shock events can either be (1) positive or negative, (2) expected or unexpected and (3) originate on the organizational or personal level (Lee, Mitchell, Holtom, McDaneil, & Hill, 1999). Several decision paths that can be taken by IT professionals have been proposed by Lee and Mitchell (1994).

The unfolding model of voluntary turnover has been mentioned by several IT as well as general turnover related literature reviews as a possible area for future research (Allen et al., 2014; Holtom, Mitchell, Lee, & Eberly, 2008; Joseph et al., 2007). According to Joseph et al. (2007), IT turnover research should focus on understanding events that trigger the turnover of IT professionals. Recent IT turnover literature has employed and contributed to the unfolding model of voluntary turnover. Niederman et al. (2007) have found additional decision paths that are especially relevant to the IT domain. Mourmant and Gallivan (2007) focused on the influence of personality on taking different decision paths. There are a few studies that employed the unfolding model of voluntary turnover to analyze the turnover of IT professionals that have the aim of founding an own company (Mourmant, Gallivan, & Kalika, 2009; Mourmant & Voutsina, 2010, 2012). However, it still remains unclear what are possible shock events that are specific for ITO vendors.

An event that is theoretically considered is project failure which is a quite common event in the IT domain (The Standish Group, 2013). A project failure evokes negative emotions, such as frustration, disappointment, depression, anger or doubts about one's work (Shepherd & Cardon, 2009; Shepherd, Haynie, & Patzelt, 2013; Shepherd, Patzelt, Williams, & Warnecke, 2014; Shepherd, Patzelt, & Wolfe, 2011). These emotions should be strong enough to trigger the decision processes of turnover. Employing the categorization of Lee and Mitchell (1994), a project failure is a shock that is (1) seen negatively by the individual, (2) mostly unexpected, as individuals normally do not expect the failure at project start, and (3) originates on the organizational level.

Another interesting aspect is the influence of the social network of the IT professional on turnover. Junglas, Armstrong, Goel, and Harris (2013) focus on the relationship between the personal network of an IT professional and the turnover intention, but they only consider the external network and do not consider the relationships within an IT company. A study in the management literature performed by Krackhardt and Porter (1986) analyzed the turnover of employees in fast food restaurants and found that turnover occurs in clusters. They found that employees have a higher probability of turnover, if another employee with a perceived similar position within the social network have conducted turnover. Felps et al. (2009) analyze the turnover of employees of a retail bank. They found that the job search behavior of co-workers increases the probability of turnover. However, neither Felps et al. (2009) nor Krackhardt and Porter (1986) analyzed directly how turnover spreads within a larger social network and do not consider IT professionals.

Regarding practice, IT managers are keen on preventing turnover and retaining IT professionals that think about leaving. Turnover and retention are actually two sides of the same coin, so to speak: by understanding the factors that lead to turnover, retention actions can be developed. However, choosing the best actions to retain an IT professional is not straightforward. Cost and time restrictions may preclude using all possible retention actions, that have been previously discussed, and individuals respond differently to the various actions. Therefore, a one-size-fits-all strategy does not work. It remains unclear which retention strategy should be taken for a specific group of IT professionals.

RQ3: Which constructs should be part of a new analytical framework of IT outsourcing?

The choice of IT outsourcing contract type influences project performance (Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003) and mostly determines the governance structure. It has already been analyzed by a few studies (Gefen et al., 2008; Gopal et al., 2003; Kalnins & Mayer, 2004). As previously mentioned, most of these studies focus on transaction cost economics (TCE) to explain the choice of the contract, but recent studies rise doubts about the applicability of TCE (Karimi-Alaghehband et al., 2011; Lacity et al., 2011; Schermann et al., 2016). Lacity et al. (2011) respond by a call for the development of an own analytical framework for the ITO domain. However, it remains unclear, which constructs should be part of such a new analytical framework.

TCE is often criticized for only looking at individual transactions and not considering the broader context of the transaction (Aubert, Houde, Patry, & Rivard, 2012; Lacity et al., 2011). For instance, TCE does not consider the ITO strategy of the customer, which has already been mentioned by several researchers (Carter & Hodgson, 2006; Lacity et al., 2011; Nam, Rajagopalan, Rao, & Chaudhury, 1996). Therefore, a multi-level approach should be taken for the development of a new theory of ITO.

Schermann et al. (2016) analyzed the influence of uncertainty on contract choice and have found that the relevance of TCE has changed over time. It seems to be irrelevant after the year 1999. A central assumption of TCE is the danger of opportunistic behavior. However, it remains unclear whether this factors has changed as well over time in the ITO market.

These three research questions have been chosen, among other reasons, due to the unique data set that builds the basis for this dissertation. Other research areas would have been possible, but the three research areas have been chosen due to specific reasons. Regarding research question 1, the data set contains data on every member of all project teams. Therefore it is possible to analyze team factors that require data on every team member, which is the case when analyzing subgroups.

Turnover has been chosen as a research field for research question 2, because the data set contains real turnover incidents. Most studies on IT turnover focus on turnover intention although empirical results show that there is only a marginal relationship between actual turnover and turnover intention (Joseph et al., 2007; Maier, Laumer, Eckhardt, & Weitzel, 2015). Additionally, due to the longitudinal data on each employee, it is possible to analyze factors that have led to the turnover case.

The topic of research question 3 has been mainly chosen due to the possibility offered by the data set to carry on previous research by the chair: Schermann et al. (2016), Dongus, Yetton, Schermann, and Krcmar (2014) and Hoermann et al. (2015). The data set contains detailed information on a large number of projects. This makes it possible to analyze new constructs that influence the choice of IT project governance.

I will cover other possible promising research areas offered by the data set in part 5.2 in addition to areas for future research in the three covered research areas.

4. Research Strategy

The chosen research strategy was mostly influenced by the unique data set that forms the basis for this thesis. In the following, this data set will be described in detail. Then, the research strategy will be outlined and the chapter ends with the different quantitative and qualitative methodologies that have been employed in this dissertation.

4.1 Employed Data Set

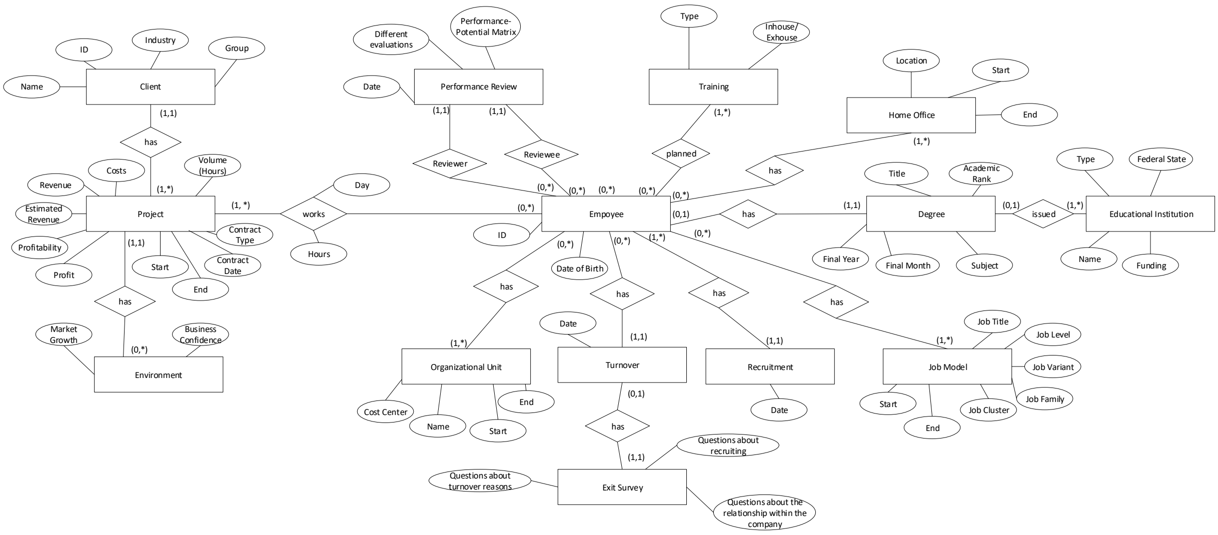

Figure 3. Entity Relationship Model of the data set (can also be found in the Appendix)

This thesis is mostly based on a large archive data set that was provided by a leading German ITO vendor, which is called ALPHA due to confidentiality reasons. The data set comprised about three gigabyte of structured data that has been extracted directly from the project management and human resource management systems. ALPHA is among the 10 largest ITO vendors in Germany and is a company with a solid reputation in the industry. The company focuses on establishing and maintaining good working relationships with its professionals. Since it has been founded, ALPHA has pursued a growth strategy. It generates most of its revenue through consulting projects, software development and large application hosting projects for clients from various industries including insurance, banking and automotive.

Due to its origin, the data set can be grouped into two subsets. The first one comprises information about all 55.397 projects that have been conducted between 1995 and 2014. Over these years, 25.906 projects have been conducted for 1.999 different customers. The remaining projects are internal projects of ALPHA. Projects last on average about 210 days and the typical team size is around 4.4 professionals. The data set contains information on the customer of the project size, the project duration, the contract type, the profit margin of the project and the overall revenue of the project.

The second subset comprises information about the more than 8.000 employees that have worked for ALPHA between 1995 and 2014. However, some of the information is only available after 2008, because new human resource management were introduced at that time. There is information on age, gender, entry and exit date, received trainings, yearly performance review, organizational unit, job type and the home office.

These two subsets are linked through a large table that stores the information which employees have worked how many hours for which project on a daily basis. This information enables to track the working life of an employee longitudinally.

Additionally to this structured data set, ALPHA provided access to a survey that has been conducted between January 2008 and May 2013. The survey has been sent to employee that have handed in their termination letter. In total, ALPHA received 302 completed surveys. The survey contains 41 questions and is structured into general questions about the organization, questions regarding the turnover, questions regarding the personal relationships within the organization and questions regarding the turnover reasons and possible retention actions that could have worked.

4.2 Research Approach

According to Creswell (2018), a research approach consists of three parts: the epistemological position, the procedure of inquiry and the specific research methods. A similar structure has been used by Orlikowski and Baroudi (1991) who additionally considered the time frame of the study. The decisions regarding the epistemological positon, the procedure of inquiry, the time frame of the study and the specific research methods made for this dissertation are presented in the following.

4.2.1 Epistemological Position

Epistemological positions describe general philosophical orientations about the world and the nature of a study (Creswell, 2018). They describe different views about knowledge and knowledge generation (Hirschheim, 1985). The following different types of epistemological positions exist (Chua, 1986; Creswell, 2018; Orlikowski & Baroudi, 1991).

Positivist Research: It dates back to the 17^{th} century and most of current IS research can be assigned to this epistemological position (Hirschheim, 1985; Orlikowski & Baroudi, 1991). It mostly originates from the natural sciences (Creswell, 2018). Positivist research assumes the existence of fixed cause-and-effect relationship that can be examined with hypotheses (Orlikowski & Baroudi, 1991). The researcher focuses on discovering these relationships as a neutral observer (Hirschheim, 1985). He begins with a theory, develops hypotheses, collects data, tests the hypotheses based on the collected data and finally supports the theory or suggest adjustments to the theory (Orlikowski & Baroudi, 1991).

Interpretive Research: As positivist research is problematic when applied to social sciences, interpretive research emerged (Hirschheim, 1985). It assumes that the researcher interacts with the world around him and creates his own subjective meaning of the world (Creswell, 2018). Therefore, the researcher tends to influence the obtained insights. The aim is not to reach generalization while conducting research, but to understand the deeper structure and relationships within a certain phenomenon (Orlikowski & Baroudi, 1991). Normally, interpretive research is conducted in the natural setting of the phenomenon (Orlikowski & Baroudi, 1991).

Critical Research: It focuses on critiquing the current status by outlining the contradictions within the current social system. It is based on interpretive research, but additionally contains an action agenda and persues a much more active role (Creswell, 2018). The aim is to create awareness and to transform these social conditions (Orlikowski & Baroudi, 1991). Critical research is change oriented and often has a political agenda (Creswell, 2018). According to Orlikowski and Baroudi (1991), this epistemological position is very rare in IS research.

Pragmatic Research: This epistemological position has developed in recent years (Creswell, 2018). Rather than focusing on a specific philosophy, it considers the problem that is addressed by the researcher and takes the philosophy that works best. It is also possible to combine the previously discussed epistemological positions. Researchers pragmatically choose multiple methods, have different assumptions, and use different forms of data collection and analysis. Scientific truth is what works at a time (Creswell, 2018).

This dissertation follows a pragmatic research epistemological position. The focus is on considering the research problem and choosing the research method and assumptions that work best. However, due to the heavy focus on the archive data set and testing hypotheses with it, this dissertation is also close to positivist research. Quite often theories that have their roots in domains outside IS research are tested in an IS context based on predefined theories.

4.2.2 Procedures of Inquiry

A broad variety of different procedures of inquiries, which are also often simply referred to as "groups of research methods", are employed in IS research (Robey, 1996; Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008). However, there is the tendency to focus on behavioral research methods (Ayanso, Lertwachara, & Vachon, 2007; Orlikowski & Baroudi, 1991; Palvia et al., 2004). Contrary to that, "Wirtschaftsinformatik", which is the German pendant to the Anglo-American IS research, mostly employs constructive research methods (Wilde & Hess, 2007). However, in recent years there seems to be a trend in the "Wirtschaftsinformatik" community towards more behavioral research methods (Schreiner, Hess, & Benlian, 2015; Wilde & Hess, 2007).

There are different ways how research methods can be categorized. Wilde and Hess (2007) that focus exclusively on "Wirtschaftsinformatik" distinguish research methods along two dimensions: behavioral vs. constructive and qualitative vs. quantitative. Creswell (2018) does not consider the behavioral vs. constructive dimension and simple distinguishes between quantitative methods, qualitative methods and mixed methods that will be discussed in the following.

Quantitative methods: The majority of studies in information systems research fall into this category (Orlikowski & Baroudi, 1991). These methods most of the time test theories deductively by analyzing the relationship between variables of that theory (Creswell, 2018; Gephart, 2004). The variables are typically measured as numbered data which makes the application of statistical tools possible (Creswell, 2018). The written report of a quantitative study has a clear structure: introduction, literature, theory, methods, results, discussion (Creswell, 2018). The decision whether to conduct a study with a quantitative or a qualitative method depends among other reasons on the current state of literature on a given topic. A quantitative approach is more likely for research on established phenomenon (Bluhm, Harman, Lee, & Mitchell, 2011). It has the advantage of generalization, but requires access to relevant data (Gephart, 2004).

Qualitative methods: It has gained popularity in research in the second half of the 20th century (Creswell, 2018). Myers (1997) described it as being still relatively new in information systems research in 1997. It is mostly used for exploring and understanding new or not well researched social phenomenon that are often associated with individuals or groups (Creswell, 2018; Myers, 1997). Qualitative methods focus on an inductive style and follow the philosophy to reason from particulars to general (Creswell, 2018). Unlike with studies with quantitative methods, no fixed structure for the report exists (Creswell, 2018). In contrast to quantitative methods, qualitative methods are inductive and interpretative (Gephart, 2004).

Mixed methods: It is considered to be the third group of research methods, beside quantitative and qualitative methods (Ridenour & Newman, 2008). Mixed methods should be differentiated from multi methods. Multi methods employ two or more different methods in one paper, but, unlike mixed methods, it is not necessary that quantitative as well as qualitative methods are used (Venkatesh, Brown, & Bala, 2013). Mixed methods are therefore a special form of multi methods. Due to the various possibilities to combine quantitative and qualitative methods, different designs for mixed methods studies exist (Creswell, Plano Clark, Gutmann, & Hanson, 2003):

1. *Sequential Explanatory Design*: After having finished a quantitative study, a qualitative study is conducted. The main goal of the qualitative study is to find explanations for relationships that have been discovered in the quantitative study.
2. *Sequential Exploratory Design*: This design is similar to the Sequential Explanatory Design, but this time the qualitative study is conducted first. The main goal is to explore a phenomenon qualitatively and then test it with a quantitative study.
3. *Sequential Transformative Design*: There are two possible sequences: either a quantitative study is followed by a qualitative study or a qualitative study is followed by a quantitative study. The main difference to the first two designs is that an overall theoretical perspective is present. The main goal is to employ two suitable methods that allow the researcher to analyze the theoretical perspective.
4. *Concurrent Triangulation Design*: Quantitative data as well as qualitative data is collected and analyzed concurrently. The aim is to determine whether there are similarities or differences between the quantitative study and the qualitative study.
5. *Concurrent Nested Design*: This design has one dominant study, which can be qualitative or quantitative. The second study has just a supporting role and is embedded in the dominant study. The advantage of this design is that the supporting study addresses weaknesses of the dominant study to gain a broader perspective.
6. *Concurrent Transformative Design*: This design is similar to the Sequential Transformative Design, but in this case the two phases are conducted concurrently and not sequentially.

The choice of the mixed methods design should be based on the research question that is answered (Venkatesh et al., 2013). Another important aspect is the consideration of time that is available for collecting data, as a sequential design takes longer than a concurrent one (Creswell et al., 2003).

According to Venkatesh et al. (2013), a mixed methods approach has three values for IS research. First, they have the advantage that it is possible to analyze confirmatory and exploratory research questions at the same time. Although exceptions exist, quantitative methods have been typically used for confirmatory research questions and qualitative methods typically for exploratory research questions in IS research (Venkatesh et al., 2013; Walsham, 2006). As new phenomena of interest to research emerge constantly in IS, a mixed methods approach is especially valuable IS research, as it is possible to explore and confirm aspects of the new phenomenon. Second, a mixed methods approach provides stronger inferences than just a qualitative or quantitative approach. Specific research methods have their strengths and weaknesses. A mixed methods approach makes it possible to overlap the weakness of one research method with a strength of the other one. Third, a mixed methods approach provides the opportunity for a greater range of divergent or convergent insights. Finding convergent insights improves the understanding of the researched phenomenon and opens up new avenues for future research (Venkatesh et al., 2013). The third advantage of mixed methods is especially of value regarding the call in IS research to conduct more replication studies, as less than half of the results in social science cannot be replicated (Dennis & Valacich, 2014).

This dissertation relies on behavioral research methods. Due to the available data set, there is a focus on quantitative methods, but also mixed methods approaches have been used to answer the research questions. In the following, I discuss the strategy of inquiry for each research question.

Research Question 1 ("How do subgroups form and what is their influence on the performance of ITO projects?"): A mixed methods approach has been used to answer the first research question. It is possible to analyze the influence of subgroups on project performance with quantitative methods based on the data set, but it is not possible to analyze the formation of subgroups within IT project teams. Therefore, a qualitative approach was chosen for this analysis. The main focus of this research question is to analyze the influence of subgroups on project performance, but also the question how they form should be addressed. Due to this a concurrent nested mixed-method approach has been chosen with a main quantitative approach and a supporting qualitative approach. In this case a mixed methods approach has the advantage that the weaknesses of the quantitative study are addressed with a qualitative study.

Research Question 2 ("Is turnover influenced by external events and retention strategies?"): This research question focuses on quantitative research methods. Due to the longitudinal perspective on each employee and the work related information that is available in the data set, it is possible to analyze quantitatively the influence of shock events on turnover. A concurrent triangulation mixed methods approach has been chosen to analyze retention strategies for IT professionals. The data set comprises a survey of employees that have announced that they are leaving the organization. This survey is analyzed quantitatively in order to develop retention strategies. A qualitative study has been conducted additionally to triangulate the findings of the quantitative analysis of the survey.

Research Question 3 ("Which constructs should be part of a new analytical framework of IT outsourcing?"): This research questions uses quantitative research methods to find constructs with high explanatory power in the data set. Although exploratory research questions are normally answered with qualitative studies (Venkatesh et al., 2013; Walsham, 2006), it is possible to answer this research question with a quantitative approach, because the data set contains a large number of different variables. The aim is to find surprising anomalies for variables with an influence on the contract choice for IT outsourcing projects. Surprising anomalies in data are often the starting point reasoning process that leads to theory building (Peirce, 2012; Van de Ven et al., 2015). Two things are important during this process (Van de Ven et al., 2015). First, it is important to ground the surprising anomaly in reality and in the existing literature. Second, the surprising anomaly has to be interesting and important for advancing the current understanding of the phenomenon.

4.2.3 Time Frame of the Study

It is possible to distinguish four different categories: cross-sectional with a single snapshot, cross-sectional with multiple snapshots, longitudinal, and process traces (Orlikowski & Baroudi, 1991). Cross-sectional studies can either have a single snapshot or multiple snapshots over time. For instance, a survey can be carried out only once or regularly on a yearly basis, such as the "Sozio-ökonomische Panel" in Germany (DIW, 2018). Longitudinal studies differ from cross-sectional studies with multiple snapshot as they uninterruptedly examine a phenomenon over a longer time period. Process traces, such as analyzing a protocol of a meeting or an experiment with a problem solving task, employ continuous data collection, but are not truly longitudinal as the studied event only lasts for a few hours.

This dissertation contains studies with a single snapshot, cross-sectional approach as well as studies with a longitudinal approach. The conducted case studies in research question 1, the expert interviews in research question 2 and the cluster analysis in research question 2 have a cross-sectional approach with single snapshots. All other studies have a longitudinal approach as they are based on the described data set. The data set uninterruptedly contains information of the conducted projects and the involved employees.

4.2.4 Research Methods

As this dissertation followed partly a mixed-method strategy of inquiry, quantitative as well as qualitative research methods have been employed. The different research methods that have been employed by publications of this dissertation are generally described in the following two sections. The detailed description of the research methods can be found in the publication.

4.2.4.1 Quantitative Methods

Regression Analysis: Regression analysis describes a set of different statistical analysis procedures for evaluating the relationship between one dependent variable and one or several independent variables (Backhaus, Erichson, Plinke, & Weiber, 2018; Sen & Srivastava, 2012). It can be used to examine the relationship between variables quantitatively and also to estimate the dependent variable based on a set of independent variables (Sen & Srivastava, 2012).

If the dependent variable is continuous, linear regression analysis can be employed. The model has the following general form:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_j x_j + u$$

with y as the dependent variable, β_0 as the intercept, β_j as the coefficient of variable x_j and u as the error term.

A regression analysis has the following five general steps (Backhaus et al., 2018):

1. *Specifying regression model*: An important issue during this step is selecting the independent variables that should be included in the model. Some of the variables are obviously included, because they have to be part of the model in order to test a specific hypothesis. However, selecting an appropriate set of control variables is more complicated. A control variable should be correlated with the dependent variable, but there should also be a causal relationship.

2. *Estimating regression function*: This step estimates the β_i of the regression in a way that the the individual error term u is minimized. One way to do this, is the ordinary least squares (OLS) approach, that minimizes the sum of the squared residuals (Sen & Srivastava, 2012).

3. *Assessing regression function*: The regression function as a whole is assessed regarding its goodness of fit. Different statistical measures such as the R-squared, adjusted R-squared or F-statistic can be used.

4. *Assessing regression coefficients*: The null hypothesis, whether the coefficient fulfills $\beta_i = 0$, is assessed during this step. This can be done with a t-test or a z-test. If the test shows that the p-value is smaller than a certain value called α, the null hypothesis is rejected. Normally, values of 0.1 or 0.05 are used for α.

5. *Assessing model assumptions*: Depending on the type of regression analysis, different model assumptions have to be fulfilled. A linear regression model assumes the following:

    1. The model is correctly specified: (a) coefficients β_j are linear; (b) the relevant variables are part of the model; and (c) the number of parameters is smaller than the number of observations.

    2. The expected value of the error term is zero.

    3. There is no correlation between the error term and the independent variables.

    4. Homoscedasticity: The error term has a constant variance.

    5. No autocorrelation: The individual error terms are not correlated.

    6. No multi-collinearity: There is no linear dependency between the independent variables.

    7. The error term is normally distributed.

However, normal linear regression analysis is not possible for panel data, because the assumptions of homoscedasticity and no autocorrelation are violated (Greene, 2003; Wooldridge, 2010). Panel data is present when there are several observations of the same entity over time. It is possible to add an effect to each observation to address the violated assumptions. A random effect model is a special form of a hierarchical linear model and assumes that the model parameters are random variables (Greene, 2003; Wooldridge, 2010). There is a random intercept for each observation. A fixed effect model assumes that the model parameters are fixed (Greene, 2003; Wooldridge, 2010). There is one time-invariant intercept for each subject.

Logistic regression analysis: If the dependent variable is binary, logistic regression analysis has to be used (Backhaus et al., 2018). Linear regression analysis cannot be used in this case, because the assumption, that the error term is normally distributed, is violated. However, the previously described five general steps can also be used in this case.

The model has the following general form (Backhaus et al., 2018):

$$P(Y = 1|x_1, \dots, x_j) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_j x_j)}}$$

with $P(Y = 1|x_1, \dots, x_j)$ as the conditional probability of event 1 for given values of the independent variables $x_1, \dots, x_j$. In order to estimate this relationship the maximum likelihood method is employed instead of the OLS method in linear regression (Backhaus et al., 2018). As the coefficients do not have a linear influence in the logistic regression model, it is not possible to interpret the magnitude of their influence. However, it is possible to interpret the direction of the relationship (Backhaus et al., 2018).

General Additive Models (GAM): Linear regression analysis assumes a linear influence of all independent variables. However, one independent variable might have a non-linear influence. GAM offer the possibility to model the non-linear influence of one or several independent variables. GAM assume that the dependent variable *y* has an exponential family distribution (Rigby & Stasinopoulos, 2005). It models the mean of *y* as a function of the independent variables. The variance, the skewness and the kurtosis of *y* are functions of a constant factor (Rigby & Stasinopoulos, 2005). GAM is an extension of generalized linear models where the linear form of the explanatory variables $\sum \beta_i X_i$ is replaced by a sum of smooth functions $\sum f_i(X_i)$ (Hastie & Tibshirani, 1986). It is possible to use several different link functions, which makes it possible to analyze a binary dependent variable (Hastie & Tibshirani, 1990). The previously described five general steps of linear regression analysis can also be used for general additive models.

Survival Analysis: The term “survival analysis” describes a group of statistical methods that can be used to analyze time-to-event data (Martinussen & Scheike, 2006). Originally, survival analysis was used to analyze the survival times of patients in a medical environment, i.e. the time until death (Bellera et al., 2010; Fisher & Lin, 1999; Fox & Weisberg, 2011; Martinussen & Scheike, 2006). The field is therefore still referred to as “survival analysis” (Bellera et al., 2010; Fisher & Lin, 1999). Despite its medical legacy, survival analysis can be used to analyze the time to almost any kind of event that can be described in binary terms, i.e. either “the event happened” or “the event didn’t happen” (Morita, Lee, & Mowday, 1989). Examples for such an event are e.g. the failure of machines, a promotion, or the moment a specified level of organizational performance is reached (Fisher & Lin, 1999; Morita et al., 1989). Survival analysis considers the influence of the independent variables on the time till a binary event occurs (Fox & Weisberg, 2011). As an example, survival analysis could be used to look into the effect of certain personal characteristics (e.g. age, gender, weight) or medical treatments on the survival times of patients (Fisher & Lin, 1999). Morita et al. (1989) provide one of the first applications of survival analysis in turnover research. More recent examples have been published e.g. by Ballinger, Lehman, and Schoorman (2010), Gopalakrishnan, Halgin, and Borgatti (2013), Joseph et al. (2015), and Mossholder, Settoon, and Henagan (2005). For performing a survival analysis, the previously described five general steps can be used.

A common challenge in survival analysis is that data may be incomplete, so called censored data (Martinussen & Scheike, 2006). A number of situations can lead to data being fragmentary. In clinical study, for examples, patients may survive past the pre-defined end of the study period or move to another city where their health status can no longer be tracked (Fox & Weisberg, 2011; Morita et al., 1989). In the context of turnover research, data can be incomplete when employees joined the organization prior to the start of the study period or stay after the end of the study period. Dismissing all censored data can greatly reduce the data foundation and thus be a very impractical solution, in particular for longitudinal studies (Martinussen & Scheike, 2006). In addition, censored data does offer a valuable contribution to survival analysis – even though the data may not specify the exact time of the event happening, it does imply that the event did not happen until a known point in time (Bellera et al., 2010). Therefore, most survival analysis models can incorporate censored data and use the information gained from the data that is available to estimate the survival and hazard functions (Morita et al., 1989).

A well suited approach for analyzing turnover are Cox proportional hazard models (Cox, 1972). First, they allow the usage of time dependent independent variables (Martinussen & Scheike, 2006). Second, Cox proportional hazard models allow censored survival data (Moore, 2016). Third, they do not require assumptions about the baseline survival distribution (Moore, 2016).

Cluster Analysis: In contrast to the previously discussed statistical method, cluster analysis is a structure discovering multivariate method and not a structure testing multivariate method (Backhaus et al., 2018). The main goal of cluster analysis is to partition all observations into a certain number of groups by simultaneously considering all the available variables (Backhaus et al., 2018; Ketchen & Shook, 1996).

A cluster analysis consists of three steps (Backhaus et al., 2018; Ketchen & Shook, 1996):

1. *Determining clustering variables*: During the first step, it is necessary to determine which covariates should be used for forming the clusters. Variables have to be standardized in order to give them equal weight and importance during the formation of the clusters (Ketchen & Shook, 1996). Another issue that has to be considered is multi-collinearity between certain variables, because it might overweight the influence of certain clustering variables (Ketchen & Shook, 1996).

2. *Selecting clustering algorithm*: Several different algorithms for clustering the research objects exist. In general, there are two basic types of algorithms: hierarchical and nonhierarchical (Backhaus et al., 2018; Ketchen & Shook, 1996). Hierarchical clustering algorithms build a tree-like structure by either adding elements to or deleting

elements from a cluster. Nonhierarchical clustering algorithms first select initial center points for each cluster and then assign the observations to the cluster with the nearest center point. While new observations are assigned, the center points are recomputed.

3. *Determine number of clusters*: The last step determines the stopping criteria for the clustering algorithms. The decision is a trade-off between manageability (low number of clusters) and homogeneity within the clusters (high number of clusters) (Backhaus et al., 2018). Different statistical as well as non-statistical methods exist for determining the appropriate number of clusters. As each method has limitations, a combination should be used for determining the number of clusters (Ketchen & Shook, 1996).

4.2.4.2 Qualitative Methods

Case Study Research: A case study is a research strategy which aims at understanding the dynamics of a contemporary phenomenon in its real-life context (Eisenhardt, 1989; Yin, 2014). The following steps give a short overview on how to conduct a case study. A detailed description can be found in Yin (2014):

1. *Plan*: This step mostly considers the question whether case study research is an appropriate research strategy for a particular study. Case study research should be used when the research question focuses on "how" and "why", the investigator has no control over event and a contemporary phenomenon in a real-life context should be analyzed (Yin, 2014). According to Eisenhardt (1989), case studies can provide description, test theories and generate theories. They also have the advantage that it is possible to use various sources of information. It is possible to use quantitative evidence such as questionnaires or frequency counts as well as qualitative evidence like interviews and observations (Yin, 2014).

2. *Design*: The following general components should be considered during the design of a case study: (1) a study's research questions; (2) it's propositions, if any; (3) its unit(s) of analysis; (4) the logic linking the data to the propositions; and (5) the criteria for interpreting the findings (Yin, 2014). Yin (2014) mentions four different types of case studies based on a 2x2 matrix with the dimensions: single-case design vs. multiple-case design and single-unit of analysis vs. multiple units of analysis.

3. *Prepare*: This step is about the preparations that are necessary for collecting case study evidence. The investigator should have the required skills for conducting the case study and train for the specific case study (Yin, 2014). According to Yin (2014), a case study protocol is a useful measure to stay focused on the goals of the case study. It contains the hypotheses and propositions as well as the theoretical framework, the data collection procedures, the case study questions and an outline of the case study report. In order to prepare the case study thoroughly, conducting a pilot study might be advisable. Case selection is an important issue, especially if a theory should be built (Eisenhardt, 1989).

4. *Collect*: During this step, the data for the case study is collected. Various different sources of evidence that can be used, such as documentation, archival records, interviews, direct observations, participant-observation and physical artifacts (Yin,

2014). The following three principles help to establish construct validity and reliability: (1) Use multiple sources of evidence; (2) Create a case study database; and (3) Maintain a chain of evidence.

5. *Analyze*: Yin (2014) names the following four general strategies for analyzing the collected case study evidence: (1) Relying on theoretical propositions; (2) Developing a case description; (3) Using both qualitative and quantitative date; and (4) Examining rival explanations. The following five analytical techniques should be considered during this step: (1) Patten Matching; (2) Explanation Building; (3) Time-Series Analysis; (4) Logic Models; and (5) Cross-Case Synthesis.

6. *Report*: This step is about composing the previous made conclusions and findings. First of all, it is necessary to define the audience of the case study, as each one has different needs (Yin, 2014). An important issue is the question whether to make the case and/or the individual persons anonymous. It is advisable to have a rich description of the case to enable the reader to reach own conclusions (Yin, 2014).

Expert interviews: According to Gläser and Laudel (2009), experts are persons that have special knowledge about a specific issue. Expert interviews is a research method that translates the research question into interview questions, reveals this knowledge and makes it accessible for subsequent analysis (Gläser & Laudel, 2009). Expert interviews as a research method consist of the following four steps (Gläser & Laudel, 2009).

1. *Research question and preparations*: The first step is the formulation of a relevant research questions and of a set of questions that guide the whole research process (Gläser & Laudel, 2009). It has to be decided whether a structured interview, a semi-structured interview or a non-structured interview should be conducted. Depending on this decision, the interview guideline or questionnaire has to be prepared.

2. *Expert interviews*: Experts for interviews should be selected based on their knowledge regarding the research topic, their ability and willingness to express the knowledge and their availability (Gläser & Laudel, 2009; Gorden, 1975). It is possible to conduct the interview via telephone or face-to-face, which has the advantage that the non-verbal conversation is not lost, but it increases the travel effort. Gläser and Laudel (2009) suggest a few rules that should be obeyed during the interview: (1) Listen actively; (2) Ask flexibly; (3) Clarify things you did not understand; (4) Ask for details; (5) Ask short and clear questions; (6) Show Competence; and (7) Avoid evaluation. The interview should be recorder and later transcribed, but it is necessary to ask the interviewee for permission.

3. *Qualitative content analysis*: During this step, the previously created transcriptions are analyzed. This can be done with grounded theory methodology techniques (Wiesche, Jurisch, Yetton, & Krcmar, 2017).

4. *Interpretation of results and publication*: The results of the qualitative content analysis are interpreted in order to answer the research question. The structure of the publication is dependent on the audience of the study. Gläser and Laudel (2009, p. 268ff.) suggest a basic structure, which is similar to the structure suggested by Yin (2014).

5. Research Studies

In the following paragraphs, we summarize the seven publications embedded in part B1 – Accepted Publications and part B2 – Publications under Review. In doing so, the research problem, the methodological approach, and the main contributions of each publication (P) are briefly outlined. All accepted papers can also be found in the appendix in their original version.

No.	Authors	Title	Outlet	Type
P1	Pflügler, Wiesche, Krcmar	Subgroups in Agile and Traditional IT Project Teams	HICSS 2018 (accepted)	CON (VHB: C)
P2	Pflügler, Jäschke, Mälzer, Wiesche, Krcmar	"Do I Want to Have Losers In My Team?" – A Quantitative Study of Learning from IT Project Failure	HICSS 2018 (accepted)	CON (VHB: C)
P3	Pflügler, Wiesche, Krcmar	The Dual-Sided Effect of Project Failure on IT Professionals	ACM SIGMIS CPR 2016 (accepted)	CON (NR)
P4	Pflügler, Becker, Wiesche, Krcmar	Strategies for Retaining Key IT Professionals	MISQE (accepted)	JNL (VHB: B)
P5	Pflügler, Wiesche, Krcmar	The Explanatory Power of the Constructs of Transaction Cost Economics Theory	IRWITPM 2016 (accepted)	CON (NR)
P6	Pflügler, Wiesche, Krcmar	Are We Already in a Mature ITO Market? A Longitudinal Study on the Effects of Market Maturity on ITO Vendor Project Performance	ICIS 2015 (accepted)	CON (VHB: A)

HICSS: Hawaii International Conference on System Sciences; ACM SIGMIS: Association for Computing Machinery Special Interest Groups on Management and Information Systems; CPR: Computers and People Research; IRWITPM: International Research Workshop on Information Technology Project Management; AOM Annual Meeting: Academy of Management – Annual Meeting; ICIS: International Conference on Information Systems; MISQE: Management Information Systems Quarterly Executive; JNL: Journal; CON: Conference; NR: Not Ranked; VHB: German Academic Association for Business Research.

Table 2. Overview on Embedded Publications that are accepted

No.	Authors	Title	Outlet	Type
P7	Pflügler, Wiesche, Krcmar	The Influence of Team and Task Familiarity within Teams on the Performance of IT Projects	ACM SIGMIS Database (Revise & Resubmit)	JNL (VHB: B)

ACM SIGMIS: Association for Computing Machinery Special Interest Groups on Management and Information Systems; JNL: Journal; VHB: German Academic Association for Business Research.

Table 3. Overview on Embedded Publications that are under review

Publications P1, P2 and P7 focus on answering research question 1 ("How do subgroups form and what is their influence on the performance of ITO projects?"). Publication P1 considers factors that lead to the formation of subgroups within IT project teams with a qualitative research approach. Publications P2 and P7 analyze the influence of three specific subgroups on project performance, namely team familiarity, task familiarity as well as members with failure experience, with a quantitative research approach.

P1: "Subgroups in Agile and Traditional IT Project Teams": In this publication, we focus on the question how subgroups form. It has been argued that heterogeneity regarding the team members of IT projects has positive influences on project success (Hoffman & Maier, 1961; Tiwana & Mclean, 2005). However, heterogeneity can also lead to the formation of subgroups. Subgroups are formed based on faultlines, which are dividing lines regarding attributes of diversity of the team members (Carton & Cummings, 2012). The way how team members interact and work together differs between projects with an agile and a traditional project management methodology (Vidgen & Wang, 2009). This difference in collaboration should influence the formation of subgroups within project teams. This publication analyzes the following research question based on case studies of two agile and two traditional projects: Which factors lead to the formation of subgroups in agile and traditional project management methods? First, we find that the formation of subgroups differs between projects with an agile and a traditional project management methodology. Second, we find that previous ties is the dominant factor in agile projects, whereas task assignment is the dominant factor in traditional projects. Location and language lead to the formation of subgroups under both project management methodologies.

P2: "'Do I Want to Have Losers In My Team?' – A Quantitative Study of Learning from IT Project Failure": Publication P2 focuses on a special subgroup within IT project teams, namely on team members that have already experienced a project failure in the past. Despite project failures being common in the IT domain (The Standish Group, 2013), research on learning from project failures on the individual level is scarce. The effects of failures are two sided. On the one hand, they evoke negative emotions among the involved team members (Shepherd et al., 2013), but on the other hand also offers the possibility to learn from the failure. However, it remains unclear whether IT professionals that have experienced a project failure learn from it and conduct more successful projects in the future. Therefore, this publication considers the following research question: "Do IT professionals learn from failed projects and perform better in future projects?" Due to having several observations for certain customers, fixed-effect linear regression models are employed to analyze whether projects with team members that have experienced a failure have a higher performance. We find that projects with team members that have failure experience have a higher performance. Based on this relationship, we conclude that IT professionals learn from failed projects and perform better in future projects. They should be seen as a valuable human asset and be recognized accordingly. In general, it is positive to have a subgroup of team members that have experienced a project failure in the past.

P7: "The Influence of Team and Task Familiarity within Teams on the Performance of IT Projects": Publication P1 has shown that previous ties is the dominant factor that leads to the formation of subgroups in agile projects. As agile projects are typical for IT and its usage has increased in recent years (Brhel, Meth, Maedche, & Werder, 2015), we take a closer look at the influence of subgroups based on previous ties between some team members. In general, Publication P7 analyzes the influence of average team familiarity, average task familiarity, distribution of team familiarity and distribution of task familiarity on project performance. The project-based workstyle and the existence of fluid teams in IT lead to differences in team and task familiarity among the team members. Previous research has already analyzed the influence of average team and task familiarity, but has disregarded the distribution of these two factors (Espinosa, Slaughter, Kraut, & Herbsleb, 2007; Huckman et al., 2009; Reagans, Argote, & Brooks, 2005). We argue that an uneven distribution of team and task familiarity lead to the formation of subgroups within the team which in turn influences the performance of the project. In this publication, we answer the following research question: "How does the distribution of team and task familiarity among team members influence IT project performance". Based on the previously described archive data set, we constructed linear regression model with random effects to account for the fact that we have several observations for a customer. In line with prior research, we find that average team as well as task familiarity has positive effects on project performance. Regarding the distribution, we find that a higher concentration of team familiarity has a positive influence, however we do not find full support for a negative relationship between higher concentration of task familiarity and project performance. We argue that a subgroup based on the strong familiarity of a few team members in comparison to the others has a positive influence, because it gives stability to the team. The familiar team members act as informal leaders of the team and therefore give structure to the team.

Research question 2 ("Is turnover influenced by external events and retention strategies?") is considered by publications P3 and P4 as well as by an unpublished study (see Part C: 1.2 Collective Turnover: How Peer Turnover Shapes IT Professionals' Decision to Leave Their Job). Publications P4 und the unpublished study are based on the unfolding model of voluntary turnover theory after Lee and Mitchell (1994) and consider possible shock events that lead to the turnover of IT professionals, namely project failures and turnover of co-workers. Publication P6 focuses on preventing the turnover of IT professionals and suggest retention strategies for different types of IT professionals.

P3: "The Dual-Sided Effect of Project Failure on IT Professionals": Project failures are common among IT projects (The Standish Group, 2013). Publication P3 has considered whether IT professionals learn from a failed project and leverage this knowledge in future projects. However, they might also lead to turnover. As a project failure evokes negative among the involved team members (Shepherd et al., 2013), it can be a shock event that triggers a thinking process about whether to commit turnover according to the unfolding model of voluntary turnover after Lee and Mitchell (1994). In this research in progress paper, we outline the following research question: "What is the relationship between project failure and turnover as well as learning from failure on the individual level?" The second part of this research question is addressed by publication P3. In this publication, we develop a theoretical model on the influence of project failure on turnover of IT professionals. First preliminary analyses based on the data set indicate that a project failure increases the probability of turnover among the involved team members.

P4: "Strategies for Retaining Key IT Professionals": Much of the literature on IT turnover is focused on finding relationships between influencing factors and turnover. However, in order to reduce the negative impacts of turnover, IT managers are more interested in strategies how to lower turnover rates and how to retain key IT professionals. Therefore, publication P6 develops retention strategies and presents it to a practice oriented community. IT professionals have different backgrounds, different motivations for working for the current employer, are in different stages of their professional career and have different relationships within the organization. Therefore, a one-size-fits-all approach regarding the right retention strategy does not work. This publication focuses on giving IT managers a framework for choosing appropriate retention strategies for different types of IT professionals. Therefore, we ask the following research question: "Which different types of IT professionals committing turnover exist and what are appropriate retention strategies for them?" To answer this question, a concurrent triangulation mixed method approach has been chosen. First, a cluster analysis of a survey among IT employees that have announced that they are leaving the organization is conducted. Second, IT managers that have experienced many turnover incidents are interviewed. We find that IT professionals differ and commit turnover due to diverse reasons. Therefore, individual retention strategies are required. In this publication, we identify seven different types of IT professionals. For each type, specific retention actions out of five general groups of retention actions are suggested. We find the following six lessons on retaining IT professionals: (1) Know Your Employees, (2) Optimize Career Opportunities and the Internal Job Market, (3) Align Retention Actions to the Organizational Context, (4) Keep the Door Open, (5) Conduct Post-entry Interviews, and (6) Financial Compensation Leads to Short-term Retention.

Publications P5 and P6 as well as an unpublished study (see Part C: 1.1 Choice of Contract Form in IT Outsourcing: A Multi-Level Model) focus the research question 3 ("Which constructs should be part of a new analytical framework of IT outsourcing?"). Publication P4 and the unpublished study analyze the explanatory power of the constructs of transaction cost economics and suggest new constructs for analyzing project governance. In publication P6, a central assumption of TCE, the danger of opportunistic behavior, is analyzed over time.

P5: "The Explanatory Power of the Constructs of Transaction Cost Economics Theory": TCE is one of the leading frameworks for analyzing the chosen project governance in ITO relationships (Dibbern et al., 2004; Klein, 2002). Recent studies about the role of TCE in ITO show inconsistent results (Karimi-Alaghehband et al., 2011; Lacity et al., 2011; Schermann et al., 2016). In order to resolve these inconsistent results, Lacity et al. (2011) call for the development of a new analytical framework. However, it remains unclear which constructs should be part of this framework. This publication analyses the explanatory power of the constructs of TCE in order to determine possible constructs for an endogenous theory of ITO.

TCE theory after Williamson (1985) consists of environmental uncertainty, behavioral uncertainty, asset specificity, and transaction frequency. This publication addresses the following research question: “How well do the individual TCE constructs explain the governance choice in ITO transactions?” To answer this research question, we employed the explanatory power of these TCE variables based on the data set of ALPHA. We find that only environmental uncertainty and transaction frequency have a high explanatory power and therefore should be considered for an endogenous theory of ITO. Behavioral uncertainty and asset specificity are only of minor relevance. The research is limited by the fact that we employed a data set from only one vendor. We contribute to the ongoing discussion on the applicability of TCE by suggesting possible constructs for an endogenous theory of ITO.

P6: “Are We Already in a Mature ITO Market? A Longitudinal Study on the Effects of Market Maturity on ITO Vendor Project Performance”: This publication considers how one central assumption of TCE, opportunistic behavior of the involved actors, has changed within the ITO market over time. Studies have found that the effect of TCE is dependent on the market maturity (Argyres & Bigelow, 2007; Dongus et al., 2014). Therefore we considered the market maturity of the ITO market in this publication. The immature phase is characterized by high uncertainty, rapid market growth, an increasing number of firms and a low market concentration. The mature phase is associated with low uncertainty, decrease of market growth to a normal rate, domination of the market by a stable number of companies and a high market concentration (Agarwal, Sarkar, & Echambadi, 2002; Klepper, 1996; Klepper & Graddy, 1990; Mazzucato & Semmler, 1999; Thorelli & Burnett, 1981; Williamson, 1975). Cusamano, Kahl, and Suarez (2015) focus on the lifecycle of service industries and argue that three phases exist: ferment, transition and mature. A similar three-phase model has been proposed by Klepper and Graddy (1990). According to Susarla and Barua (2011) and Dongus et al. (2014), the ITO market entered into a mature phase after the year 2001. They argue that the burst of the co-called “dot-com bubble” acted as an endogenous shock to change the market. We considered the market maturity in two ways. First, we analyzed how the choice of contract for new ITO relationships has changed over time. Vendors can safeguard against the uncertainty and opportunistic behavior by choosing a FP contract. In order to capture the danger of opportunistic behavior in the market, we focused on new relationships. We used the archive data set of ALPHA to analyze the development of contract choice. As a robustness analysis, we additionally calculated the market concentration of the ITO market based on a yearly published ranking of the leading German ITO vendors. We find that the ITO market has increased its maturity and can be separated into an immature phase, occurring between 1997 and 2001, a transition phase, occurring between 2002 and 2008 and a third phase which occurred after 2008. These results show that the danger of opportunistic behavior, which is a central assumption of TCE, has decreased over time in the ITO market. This raises additional doubts whether TCE is an appropriate research framework for the current and future ITO market.

Part B1 - Accepted Publications[1]

[1] The original publications have been slightly modified, including the unification of format and reference styles, the correction of spelling errors, and minor grammatical revisions The original version of the publications can be found in the appendix.

1. Subgroups in Agile and Traditional IT Project Teams

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Publication	Hawaii International Conference on System Sciences 2018 (HICSS-51)
Status	Accepted
Contribution of First Author	Problem Definition, Research Design, Data Collection, Data Analysis, Interpretation, Reporting

Table 4. Fact Sheet Publication P1

Abstract

This paper analyzes the formation of subgroups within project teams that apply agile methods and teams that apply traditional methods. Subgroups form based on faultlines, which are dividing lines regarding attributes of diversity of the team members. We conduct case studies of two agile projects and two projects with a traditional approach. We find that the formation of subgroups differs between the two methods. Task assignment is the dominant factor that leads to the formation of subgroups in traditional methods, whereas previous ties between team members is the dominant factor in agile projects. In addition, location and language lead to the formation of subgroups in both methods. Our analysis is exploratory and our data is limited to four teams. We contribute to the literature on team formation and groups in IT project teams and show that research should consider subgroups and potential consequences when examining agile and traditional software development methods.

1.1 Introduction

The success of IT projects depends, among other things, on the skills of the team members (Faraj & Sproull, 2000; Tanaka, Morimoto, Fujita, & Tsuda, 2015). However, the selection and combination of different team members is an ongoing challenge (Faraj & Sproull, 2000; Mathieu, Tannenbaum, Donsbach, & Alliger, 2014). Previous studies have found that heterogeneity among the team members increases creativity (Hoffman & Maier, 1961; Tiwana & Mclean, 2005). At the same time, the heterogeneity of team members' attributes can also lead to the formation of subgroups within the project team (Carton & Cummings, 2012; Gibson & Vermeulen, 2003). A subgroup is a subset of team members that is characterized by a unique form of a certain attribute (e.g. age, skill or status) (Carton & Cummings, 2012).

Especially IT projects that apply agile methods, like Scrum or Extreme Programming demand team heterogeneity and foster close collaboration (Brhel et al., 2015). On the contrary, teams that follow traditional project management methods are selected based on their capabilities to conduct a pre-planned task (Vidgen & Wang, 2009). Due to these differences in the way the team collaborates and the team conducts tasks, the formation of subgroups is supposed to differ between projects with agile methods and projects with traditional methods. Practitioners should consider the formation of subgroups when applying these project management methods, because they influence the performance of the project (Bezrukova et al., 2009; Bezrukova, Thatcher, Jehn, & Spell, 2012; Carton & Cummings, 2013; Meyer, Glenz, Antino, Rico, & González-Romá, 2014). Additionally, if they are aware of the possible formation of subgroups, they can initiate actions that hinder the formation, like staffing and managing the project differently.

However, it remains unclear how subgroups form in IT projects with agile and traditional methods. Due to the differences in team composition and conducting tasks, different types of subgroups form in agile and traditional IT projects, based on faultlines, which are dividing lines that are based on attributes of diversity of team members (Carton & Cummings, 2012; Lau & Murnighan, 1998). For instance, agile methods emphasize values like commitment, openness and respect (Tripp, Riemenschneider, & Thatcher, 2016). This creates a different form of exchange between the team members (Whitworth & Biddle, 2007), which in turn influences the formation of subgroups. As it remains unclear how subgroups form under agile methods and under traditional methods, it is difficult to develop actions that hinder the formation or weaken the influence of the subgroup. To address this gap, we seek to answer the following research question: *Which factors lead to the formation of subgroups in agile and traditional project management methods?*

We chose an exploratory case study design to answer this question. We analyze four IT development projects. Two projects have employed an agile method and two projects followed a traditional approach.

We find that there are differences in the formation of subgroups between agile methods and traditional methods. The primary factor that leads to the formation of subgroups in traditional projects is the task assignment. Agile teams are characterized by subgroups that are formed due to ties between team members that know each other from previous interactions. Additionally, we find that no matter if an agile method or a traditional method has been chosen, different locations and languages lead to the formation of very dominant subgroups.

This paper is structured as followed. First, we present background information on faultlines and subgroups as well as on agile and traditional project management methods. This is followed by a presentation of the chosen research method. Then, we present the results and report on the found subgroups in agile methods and traditional methods. Finally, the theoretical and practical implications as well as limitations and possible future research are discussed. The paper ends with a short conclusion.

1.2 Theoretical Background

1.2.1 Faultlines and Subgroups

A subgroup is a subset of members of a work team, which is characterized by a unique interdependence that distinguishes the subset from other members of the team (Carton & Cummings, 2012). Subgroups are formed based on faultlines, hypothetical dividing lines, which split a team into multiple, homogeneous subgroups (Lau & Murnighan, 1998). Faultlines are based on individual attributes, like education, gender or work experience. Team members, who share one or more of these characteristics, bond with each other and thus create a subgroup (Lau & Murnighan, 2005). Previous literature has already identified possible faultlines (see Table 55).

Faultline	**Description**
Demographic	Identity-based factors of team members like age, gender, race or religion (Lau & Murnighan, 1998)
Geographic	Factors related to the location or the distance between the team members (Polzer, Crisp, Jarvenpaa, & Kim, 2006)
Language/ Culture	Factors, like language, nationality or culture. Often related to geographic factors, but not necessarily the same (Carton & Cummings, 2012; Dau, 2016; Hinds et al., 2014; Lau & Murnighan, 1998)
Personality	Factors that refer to the personality of the team members, like conscientiousness, emotional stability, attitudes, beliefs, values or cognitive style (Ellis, Mai, & Christian, 2013; Rico, Molleman, Sanchez-Manzanares, & Van der Vegt, 2007; Sawyer, Houlette, & Yeagley, 2006)
Employer related	Employer related factors, like tenure, function, pay, status or decision power (Carton & Cummings, 2012; Cooper, Patel, & Thatcher, 2013; Lau & Murnighan, 1998; Rico et al., 2007)
Knowledge	Factors like education or work experience, that related to the knowledge of the team members (Carton & Cummings, 2012)

Table 5. Faultlines in Previous Literature

Within a team there might be several different faultlines, but not all of them are activated and lead to the formation of a subgroup (Jehn & Bezrukova, 2010).

Literature distinguishes three types of subgroups (Carton & Cummings, 2012). First, members of identity-based subgroups are characterized by the same characters or share similar values (Hogg & Terry, 2000). Second, knowledge-based subgroups are formed based on technical language (Homan et al., 2007). Members of this type of subgroup often share information or use this form of exchange to solve problems and tasks together (Carton & Cummings, 2012). Third, resource-based subgroups are based on the idea of group conflict theory (Esses et al., 1998) as well as on theories of inequality and organizational ranks (Blau, 1977). Members of this type of subgroup differentiate according to the ability to claim resources, such as decision power (Carton & Cummings, 2012). Therefore, resource-based subgroups often form based on the hierarchical level.

The effects of subgroups have been studied intensively, but the empirical results differ. While some studies suggest that subgroups also have positive effects for team members (Bezrukova et al., 2009; Carton & Cummings, 2013), the majority highlights their negative consequences. In general, any type of faultline may have both, positive and negative impacts (Meyer et al., 2014). Positive effects of subgroups are mainly found related to knowledge-based subgroups (Bezrukova et al., 2009; Carton & Cummings, 2013). They have the advantage that they bring different forms of knowledge into one team (Carton & Cummings, 2013).

Negative consequences are mostly related to identity-based and resource-based subgroups. Identity-based subgroups may lead to conflicts in the whole team, caused by ethnocentrism (Cramton & Hinds, 2004), especially when there are two strong subgroups of this kind in one team, which work against each other (Carton & Cummings, 2013). Resource-based subgroups in teams may lead to an asymmetry in perception of fairness and power centralization (Carton & Cummings, 2012) which disturbs the common decision making process (Sawyer et al., 2006). In general, subgroups may cause an interruption of the knowledge flow within the team, as subgroup members communicate primarily with other members of the same subgroups (Bezrukova et al., 2012). Another negative aspect is social loafing of individuals, which happens primarily in larger subgroups (Meyer, Schermuly, & Kauffeld, 2016).

Especially difficult situations and crises foster subgroups and reinforce the barriers between individuals in the project team (Meyer, Shemla, Li, & Wegge, 2015). When these negative consequences occur in software project teams, it may have serious influence on the project success.

1.2.2 Agile and Traditional Project Management Methods

Agile methods gained popularity in recent years (Brhel et al., 2015). There are several different agile methods, like Scrum, Kanban and Extreme Programming, but Scrum is by far the most used one (Scrum Alliance, 2017). These approaches focus on the social nature of software development (Whitworth & Biddle, 2007). Values like commitment, openness and respect form the footing of all agile methods and lead to a higher perception of job satisfaction within software development teams (Tripp et al., 2016). Furthermore, additional factors like team awareness and team involvement foster cohesion within the team (Whitworth & Biddle, 2007).

An important principle of agile methods is the self-management of the team (Moe, Dingsøyr, & Dybå, 2010). Flat hierarchies and the possibility to decide how to accomplish work are fundamental aspects, which give the team higher responsibility in its work life and rises again the satisfaction level (Acuña, Gómez, & Juristo, 2009). The basis for self-managing teams is a shared-decision making process, which demands respect and trust within the whole team (Moe, Aurum, & Dybå, 2012).

Communication plays a special role within agile principles (Alzoubi, Gill, & Al-Ani, 2016). Agile methods trust in face-to-face communication, whenever it is possible (Beck et al., 2001) and see continuously exchange between team members, managers and customers as an important influence factor for project success. Frequent communication between team members supports not only performance and quality (Espinosa, Nan, & Carmel, 2015), but also promotes knowledge sharing in project teams (Ghobadi & Mathiassen, 2016).

Traditional methods are different from agile methods. They have a long tradition in IT development projects and are currently still broadly used, especially in the manufacturing industry (Leffingwell, 2010; Scrum Alliance, 2017). Traditional methods are characterized by a pre-planning stage that is followed by the execution, which makes them less flexible in comparison to agile methods (Leffingwell, 2010; Vidgen & Wang, 2009). Additionally, unlike agile methods, they have a clear hierarchy within the team (Vidgen & Wang, 2009). The collaboration is less close than in an agile project team. Daily meetings are not part of the methodology like in agile methods. As the task assignment is stable in traditional methods, the team members work together with the same few persons for most of the project time (Vidgen & Wang, 2009).

1.2.3 Subgroups within Agile and Traditional Projects

The previously described differences between agile methods and traditional methods should have different influences on the activation of faultlines and therefore on the formation of subgroups. Up to now, literature has only dealt with distributed agile teams and therefore has limited the perspective to geographical distance (Persson, Mathiassen, & Aaen, 2012; Ramesh, Cao, Mohan, & Xu, 2006). First, the collaboration differs between projects with an agile and a traditional method (Vidgen & Wang, 2009). The team members work much closer together under agile methods. Second, the fix task assignment in traditional methods leads more stable structured within the team (Vidgen & Wang, 2009). Therefore, the same team members work always together whereas different ones work together in agile methods.

1.2.4 Distributed Teams as Example for Subgroups in Software Development

There is already extensive literature on virtual and distributed teams (Gilson, Maynard, Jones Young, Vartiainen, & Hakonen, 2015; Nader, Shamsuddin, & Zahari, 2009). However, this literature mostly lacks of consideration of subgroups, although geographical distribution is a factor that is likely to lead to the formation of subgroups (Gilson et al., 2015). The faultline factors in the case of virtual teams are location and language (Gilson et al., 2015; Polzer et al., 2006). Cramton and Hinds (2004) theoretically expended the faultline model of Lau and Murnighan (1998) to virtual teams, but did not empirically test their model. An exception is

Polzer et al. (2006) that analyze the activation of faultlines and subgroups in geographically dispersed teams. They found that subgroups form and that conflict is heightened and trust is decreased between the geographically dispersed subgroups. Another exception is O'Leary and Mortensen (2010) that found that geographically based subgroups weaken team identification, lead to less effective transactive memory and increase team conflict.

As this brief overview of literature on virtual and distributed teams shows, most studies miss a consideration of subgroup theories. There are a few exceptions, but none of these studies have been conducted in the IT domain or consider also other types of subgroups, like identity-based or knowledge-based subgroups.

1.3 Research Method

To analyze factors that lead to the formation of subgroups, a qualitative design has been chosen. We decided to conduct a case study to answer our exploratory research question as it allows us to investigate phenomena in depth in its real-world context (Yin, 2014). We explored the formation of subgroups in two agile IT projects and two traditional IT projects.

1.3.1 Case Selection

Table 6 shows the description of the selected cases. In general, we selected cases with a certain number of team member in order to increase the likeliness of finding subgroups (Carton & Cummings, 2013).

Teams 1 and 2 are projects with an agile method and were conducted in a German IT company. Teams 3 and 4 are projects with a traditional method and were conducted in a German financial service company.

1.3.2 Data Collection and Analysis

Team	**Project purpose**	**People**	**Locations**	**Project Management Method**	**Number of Interviews**
1	Development of a software package concerning insurance	12	1	Scrum	5
2	Development of a business process management software	19	3	Scrum	12
3	Quality management of IT processes	15	2	Traditional	8
4	Management of IT Change Requests	12	2	Traditional	3

Table 6. Selected Cases and Interviews

Table 6 shows the number of interviews that were conducted in the four analyzed teams. In Team 1 nearly half of the team has been interviewed. More than half of the team members were interviewed in Teams 2 and 3. In Team 4 only about a quarter of the team members were interviewed. Although not all team members were interviewed, we still believe to have gotten thorough insights in all of the four teams.

We used grounded theory coding techniques to analyze the data and develop the faultline categories as introduced in the results section (Wiesche et al., 2017). We based the coding categories on factors that could be possible faultlines within the project teams. The atlas.ti software package was used to support coding and analysis.

1.4 Results

1.4.1 Agile Method

The two agile teams were well-established, self-managing teams with motivated team members with a good reputation and company record of accomplishment in ISD projects. Both teams applied Scrum as agile method. We identified several faultlines and activated subgroups in each of the two teams. They are reported in Table 7.

Our results suggest that demographic faultlines like age and gender are not activated. Team 1 and 2 only had two females respectively and therefore, the formation of a gender based subgroup is unlikely. An age based subgroup is not formed, because the team members in the two agile teams have a quite similar age between 20 and 40 years.

Knowledge and education related faultlines are not activated, because experts form groups only for the discussion of a certain topic and then dissolve again. Therefore, not stable subgroup is formed.

A faultline based on functions within the team has not been activated due to the generalist-approach of agile methods, where only the roles team member, scrum master and product owner exist. However, we found that in one team the product owner has been excluded from the retrospective because of his role. He perceived himself as ostracized.

Due to the usage of user stories in agile methods that are carried out by different combinations of team members in each iteration, only temporal subgroups form for the time a user story is carried out. They then dissolve again right after finishing the user story.

In the following, we describe the most dominant subgroups that were formed due to activated faultlines.

In team 2, the most dominant subgroup was formed due to location- and language-based faultlines. Eight of the 19 team members were located on the company site in country A. The other 11 team members were located in a different company site in country B. The software developers in country B were not native speakers in the project’s dominant language, but all team members in country A were. There was a variety in the language skills in the team in country B.

Faultline	**Description**	**Acti-vated**	**Rational for Activation**
Age	Team members were in a similar age group.		Little variance
Gender	Only small share of team members was female		Not many females
Know-ledge / education	Experts assemble in groups, but only for the discussion of a topic and then separate again		Changing faultlines over time based on user stories are not stable
Function	Generalist-approach reduced number of roles, but product owner differed.		Product owner was the only one with a different role
Previous ties	Several team members had prior work (and educational) experience together.	X	The self-managed character makes it possible that the faultline is activated
Task / goal	Continuously changing tasks and therefore goals for each iteration.		Task-based subgroups are only temporary and not persistent
Geo-graphical distance	Developers work in two different offices in different countries.	X	Informal contacts are not possible
Language	Language in country A as project language, non-native speaking developers in country B.	X	Language barrier makes communication difficult

Table 7. Theoretical and activated Faultlines

The subgroup manifests in the low number of interactions between the two team locations, but also in the perception of the team members, such as explained by one developer from country A:

"These people from the other location [country B] ... If there is not really anything, which has to be done together, we work rather isolated from each other. (System Architect 02_07)"

The formation of this subgroup is mostly due to the difficulties to communicate informally by mail, phone or video chat. This hinders closer ties between team members and reduces trust and a shared understanding. One team member mentioned that it would be positive to meet the team members from the other location to get to know them on an informal basis:

"Yes, it is positive for the project when we meet in person from time to time and to see the person and not just hear the voice, or read their mails. (System Architect 02_11)"

This communication barrier not only leads to the separation of the team, but also intensifies the relationships within the two parts of the team. In team 2, the projects dominant language is that of country A. The team members from country B often discuss the unclear issues first after the daily stand-up first internally and if this has not resolved the issue with a team member from country A:

"First of all, we try to clarify issues internally, and if there is any ambiguity, we'll get back to the [country A] team. (System Architect 02_11)"

This communication barrier not only exists due to different countries, but also because of separate offices in team 1. The office with the physical scrum board is the dominant office and most of the discussions take place in this office. Team members from other offices have to actively seek being part of the discussion and not being cut off from the information flow. One member of team 1 describes this as followed:

"If you have two separate offices, discussions stay within one office. First, you ask others from the same office and this discussion is not passed on to the other office room (Software Developer 01_02)"

In team 1, the most dominant subgroup was formed due to previous ties between some of the team members. Most of these team members knew each other from previous projects, but there was also the case where two team members happened to have gone to secondary school together. It was usual for these team members to have lunch together with team members from the previous project, where they also discussed issues concerning the current project. The scrum master described this subgroup as follows:

"Yes, [we are a subgroup], definitely, it's quite normal. If you've already spent two years together, there is of course a different kind of relationship. (Scrum Master 01_04)"

The formation of this subgroup is mostly driven by the close relationships between the team members that know each other. A subgroup based on previous ties between some team members can also be found in team 2, but it is only secondary due to the strong location based subgroup.

In team 2, we additionally find a strong task based subgroup. Normally, agile software development argues for a generalist approach, where every team member is theoretically responsible for every task. However, this team has been separated into technical consultants and into business consultants.

"You certainly have this [formation of a subgroup] between the technical consultants and the business consultants. (Scrum Master 02_09)"

1.4.2 Traditional Method

The two traditionally managed teams studied were well-established teams with motivated team members. We identified several faultlines and subgroups in each of the two teams. We report on them in Table 8.

Similarly to the agile case, we find that demographic faultlines like age and gender are not activated in traditional method settings. Team 3 and 4 only had two females respectively and therefore, the formation of a gender based subgroup is unlikely. There is no strong age based faultline, because there was little variance in the age. Most of the people were between mid-thirty and end forty, with one exception in team 3, where one member was 59 years old.

A knowledge based faultline is not activated, because people are assigned to a task based on their knowledge. Therefore, the dominant faultline is task.

A faultline based on function was not activated, although such a subgroup is likely in traditional methods due to the clear hierarchy. However, we did not find a strong hierarchical in the two analyzed teams and therefore no subgroups were formed.

We find that a faultline based on previous ties is not activated, because the team members are assigned to tasks and do not collaborate closely across tasks. Due to this, although there might be previous ties, they do not lead to the formation of a subgroup.

We find, that a task-based subgroup is the dominant subgroup, if traditional methods are used. Tasks in traditional methods are different from tasks in agile methods, because they take longer and, most of the time, people do the same task throughout the project. Therefore, the assignment to a task within a project with a traditional method separates the team and hinders close collaboration between the team members, which leads to the formation of subgroups. A member of team 3 describes this as follows:

"I mean, with people with whom you have relatively little to do, you have little exchange. With these, of course, you do not have this relationship on a personal level. (IT consultants 03_01)"

Faultline	Description	Acti-vated	Rational for Activation
Age	Team members were in a similar age group.		Little variance
Gender	Only small share of team members were female		Not many females
Know-ledge / education	Experts are assigned to tasks based on their knowledge		Task is the dominant factor that leads to the activation
Function	Clear hierarchies within teams		We did not find a hierarchical structure to be present in the teams
Previous ties	There are not many previous ties		People do not collaborate closely across tasks
Task / goal	Each team member has a fixed task that does not change	X	Task-based subgroups are formed
Geo-graphical distance	Developers work in different offices in different countries.	X	Informal contacts are not possible
Language	Language is set to be English, which is known by both parties	X	The mother tongue of a large portion of the team is German

Table 8. Theoretical and activated Faultlines

Similarly to agile projects, we find that geographical distance and language are faultlines that are activated and lead to the formation of subgroups.

"Two members working on this task are in Germany and the other two in India. There are, therefore, two subgroups which result from the geographical separation of the team. (IT consultant 04_02)"

In team 3, we find that the team leader has decided that the team should have breakfast together every Monday. This team building effort has been introduced to implement a basis to exchange project related information across people that do not work on the same task.

1.4.3 Comparison of Subgroups In Agile And Traditional Methods

The results show that we find differences regarding subgroups between agile methods and traditional methods. Task-based subgroups are dominantly formed in projects with traditional methods. In agile projects, only temporary task-based subgroups are formed for the duration of specific user stories. This is due to the circumstance that tasks are different between the two methods. In traditional methods, tasks take longer and are over the entire term performed by the same persons. In agile methods however, tasks are shorter and performed by different combinations of people over time.

We find that previous ties leads to the formation of subgroups in agile methods, but not in traditional methods. In traditional methods, task-based subgroups are the dominant subgroup and separate the team into smaller parts that work on tasks. Previous ties are therefore only of minor relevance in traditional methods. Geographical distance as well as language are faultlines that are activated under traditional methods as well as under agile methods. Those are strong factors that divide the team members, because for instance it is hardly possible to build up an informal relationship with a person from another office location.

1.5 Discussion

1.5.1 Theoretical and Practical Contribution

Our results contribute to literature on agile and traditional methods. Vidgen and Wang (2009) develop a framework that can be used to guide the organization of agile software development. However, their framework disregards the possible formation of subgroups. We extend the framework of Vidgen and Wang (2009) by showing that subgroups play a role in agile software development. Our results show, that this is especially the case, when agile methods are violated. In one of the analyzed teams, the team was divided based on the kind of tasks that they had to perform. This has led to the formation of task-based subgroups. However, the division of the team based on types of tasks is not advised according to the principles of agile software development. Furthermore, geographical distance as well as language barriers lead to the formation of subgroups. As agile methods assume a co-located team, this violation leads to the formation of a subgroup. Therefore, Hossain, Babar, and Paik (2009) suggest that a scrum of scrum approach should be taken, if the team cannot be located in a single office space.

We also contribute to literature on agile and traditional methods by showing that the formation of subgroups differs between agile and traditional methods. In traditional methods, the dominant factor for the formation of subgroups is the task. Team members that have different tasks hardly interact with each other.

In general, it seems that there are less strong and severe subgroups in projects with agile methods than in projects with traditional methods. Additionally, our results suggest that IT managers use approaches, like the breakfast in team 3 to decrease the effects of the strong subgroups.

Second, we contribute to literature on virtual teams (Gilson et al., 2015; Nader et al., 2009). We find that geographical distance as well as language leads to the formation of subgroups, no matter which type of development methodology is employed. This supports the claim of virtual team literature that attributes like language and geographical distance can divide teams.

However, studies on virtual teams focus only on these attributes and mostly disregard subgroup theory (Gilson et al., 2015). For instance, Montoya-Weiss, Massey, and Song (2001) analyzed conflict management in virtual teams, but did not consider literature on subgroups or faultlines, although they can be a source for conflicts within teams (Carton & Cummings, 2012; Pelled, Eisenhardt, & Xin, 1999). Oshri, Van Fenema, and Kotlarsky (2008) analyze knowledge transfer within virtual teams, but do not consider that the flow of information is influenced by the subgroups within the team (Ellis et al., 2003). Theory on subgroups and faultlines could give these studies an alternative perspective.

This perspective has already been employed by studies on virtual teams in non IT settings (O'Leary & Mortensen, 2010; Polzer et al., 2006). We extend this to the IT domain. Furthermore, only considering geographical distance or cultural aspects as factors disregards the broader picture. We find that previous ties in agile projects and the task assignment in projects with a traditional method do additionally have an influence.

Third, we contribute to the limited research on faultlines and subgroups in the IT domain. We show that identity-based factors like gender and age do not lead to the formation of subgroups. This is opposed to previous findings in other domains (De Meulenaere, Boone, & Buyl, 2016; Yunhyung et al., 2015). We do not find support that identity-based factors like gender and age lead to the formation of subgroups. Our results suggest that this is caused by the nature of the IT section. As females are still underrepresented in IT teams, there were not enough representatives to build this form of subgroups. Women are rather integrated in the whole team and get included in other subgroups that are independent from gender. Similarly, the age structure was balanced, which hindered the formation of age-based subgroups.

We contribute to practice by outlining which factors lead to the formation of subgroups in projects with agile methods and in projects with traditional methods. Subgroups within project teams are an issue in practice, because they influence the way how the team members interact and communicate with each other (Bezrukova et al., 2012). Due to this the performance of the project is also affected by the existence of subgroups within the team (Bezrukova et al., 2009; Bezrukova et al., 2012; Carton & Cummings, 2013; Meyer et al., 2014).

There are several ways how IT project managers can address the subgroups and faultlines in their teams. For instance, they can conduct team building efforts before the start of the project. Especially in the case of a project with several sites, it is advisable that the whole team has the possibility to informally exchange and get to know each other due to the strong subgroups based on geographical distance that we have identified.

1.5.2 Limitations

First, our results are limited by the circumstance, that we did not interview all members of the team. As subgroups might be perceptional (Homan et al., 2007), it is possible that we have missed certain subgroups. However, we interviewed quite a large share of the groups, which makes it unrealistic that we missed large or strong subgroups. Second, the analyzed teams differ in size and organizational context. Due to this, it is possible that we found subgroups that are not related to the project management method, but to the setting of the project. Third, we only analyzed two project teams with agile methods and two project teams with traditional methods. Due to this limited number, it is possible that we missed subgroups that are relevant, but were not present in our cases.

1.5.3 Future Research

We only analyzed four teams from two different firms. Due to this limited setting, it was not possible to analyze the influence of different contexts on the formation of subgroups in detail. However the context could have a huge influence on the activation of certain faultlines. Future research could further address which faultlines dominate others and whether these could be affected by management practices. Studies could examine how far agile methods could reduce location-based faultlines in distributed teams in detail.

The size of the teams that we analyzed has been between 12 and 19. Future research could address this by varying the team size. Due to closer collaboration in smaller teams, it could be the formation of subgroups differs. It could be the case that task-based subgroups do not form in traditional projects, because a specific task is assigned to only one person and not to several. The formation of subgroups could also be different in larger teams. Subgroups, based on special competencies of certain team members (Wiesche & Krcmar, 2014), could form in large teams.

Up to now, we have only analyzed Scrum as a representative of agile project management methods. Future research could address other ones. For instance, the formation of Subgroups could differ in Pair Programming due to the close collaboration between two team members.

Another possible area for future research could be related to the question how subgroups are resolved in agile methods and in traditional methods. We have found that team 3 has breakfast together every Monday. One could analyze whether such team-building events are effective in resolving subgroups. Approaches to resolve subgroups could have different influences in agile and traditional projects. An event to get to know all team members might be useful in a traditional project, but not in an agile project with Scrum, because all team members know each other from the daily stand-up meeting.

1.6 Conclusion

This paper was motivated by a need to understand groups within agile and traditional IT projects. The results of the conducted case studies show that the formation of subgroups differs between the two types of projects. We find that previous ties leads to the formation of subgroups in agile methods whereas task assignment leads to strong subgroups in traditional methods.

2. “Do I Want to Have Losers In My Team?” – A Quantitative Study of Learning from IT Project Failure

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Table 9. Fact Sheet Publication P3

Abstract

This paper is motivated by a lack of research on the learning from failed IT projects of IT professionals. It remains unclear whether they learn from failed projects and conduct more successful projects in the future. We investigate this research gap with a large quantitative data set from a German IT service provider. We find that IT professionals learn from failed projects and can leverage this knowledge in the future. Therefore, they should not be seen as “losers”, but as a valuable human resource. Our research contributes to the limited research of learning from failure in IT literature. We show that results that have been obtained in other domains are transferable to the IT domain. Our research is limited by the circumstance that our data set comes from only one IT company. This is the first paper that analyzes learning from failure of IT professionals and their performance in future projects.

2.1 Introduction

IT projects have a quite high failure rate. According to studies by The Standish Group (2013), the failure rate of IT projects is higher than 60%. Although the IT market has increased its maturity (Pflügler, Wiesche, & Krcmar, 2015; Schermann et al., 2016), the failure rate has not significantly decreased over the past decade (The Standish Group, 2013). It is estimated that the cost of failed IT project is about \$3 to \$6 billion every year (Krigsman, 2012; Sessions, 2009).

Due to the high failure rate, IT employees experience project failures quite often. Failed projects not only have a financial impact, but also create negative emotions among the employees (Shepherd et al., 2013). Despite these negative effects, failed IT projects might also have a positive effect. IT employees might learn from failed projects and leverage the gained knowledge in future projects. Learning from failed IT projects on the organizational level has already been examined for instance by Ewusi-Mensah and Przasnyski (1995), but they focused on organizational learning and not on the learning of individual project members. There are studies in management literature that focused on learning from failure on the individual level (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011; Snell, 1992). For instance, Shepherd et al. (2011) analyzed learning from failed research project.

However, it remains unclear whether these results are transferable to the IT domain. In order to learn from a failure, it is necessary that a certain attention is drawn to the failed project (Eisenhardt & Martin, 2000). The failure rate of IT projects is much higher than in most other domains. Therefore, it is possible that IT employees do not pay a lot of attention to failed projects, because they are a common thing.

Additionally, it remains unclear whether IT employees can leverage the gained knowledge in future IT projects. It is possible that they have learned from a failed project, but as IT is in constant change and new technologies and trends arise quickly (Gartner, 2017), they cannot leverage the gained knowledge in future projects.

In order to address this research gap, we aim to answer the following research question: *Do IT professionals learn from failed projects and perform better in future projects?*

We answer this question with a unique data set from an IT service provider, which is called ALPHA due to confidentiality reasons. They granted us access to data from their internal project controlling and human resource management systems. We gained extensive data on all 36,413 projects conducted by ALPHA between January 1995 and April 2014 and information on more than 8,000 IT employees that worked on these projects during that period.

This paper is structured as followed. First, we present background information on learning from failure and on the success of IT projects. This is followed by the development of the hypotheses that are subsequently examined. Then, we outline the data set, the variables and the chosen research method. In the next section, we present the results of our data analysis. Finally, the theoretical and practical implications as well as limitations and possible future research are discussed. The paper ends with a short conclusion.

2.2 Theoretical Background

2.2.1 Learning from Failure

There are many different definitions of learning which focus on various aspects like change, detecting and correcting errors, improvement, knowledge or understanding (Argote & Miron-Spektor, 2011; Fiol & Lyles, 1985). For this paper we adopt the definition that learning is the development of insights, knowledge, and associations between past actions and the effectiveness of those on future actions (Fiol & Lyles, 1985). This definition focuses on the relationship between the past, present and future and defines learning as a process and not as a single event. Learning does not occur instantly, but over time (Crossan, Lane, & White, 1999). During a learning process, experience or provided information is converted into knowledge (Argote & Miron-Spektor, 2011).

It is possible to distinguish two different forms of learning, namely learning through teaching and learning by experience. Teaching is an organized from of learning and based on controlled settings (Brown & Duguid, 1991; Denton, 1998). It can occur in many forms, such as training, mentoring or coaching and normally occurs separated from the normal working place (Antonacopoulou, 2006; Denton, 1998). Learning by experience occurs during normal working tasks (Antonacopoulou, 2001, 2006). Studies argue that employees only learn abstract knowledge from training, but lack the practical experience (Brown & Duguid, 1991; Lumineau, Fréchet, & Puthod, 2011).

Learning from failure is a special form of learning by experience. In general, learning is possible from failure as well as from success (Birk, Dingsoyr, & Stalhane, 2002). Success tells what to do and failure what not to do (Nolan, 1999). However, learning from success has a drawback. A continuous series of successes motivates a firm to become specialized in these successful operations, but this makes the firm inflexible (Baumard & Starbuck, 2005; Miller, 1993). Therefore, learning from repeated successes makes failure in the future more likely (Baumard & Starbuck, 2005). A failure forces the involved individuals to critically examine the actions which lead to the failure and therefore enhance a broader understanding of the underlying relationships that have led to the failure (Cope, 2011; Shepherd et al., 2014). This gained knowledge leads to a change of behavior in similar situations in the future, which might help to prevent a failure (Cope, 2011; Cyert & March, 1963).

Many studies suggest that failure is a better source for learning than success (Cyert & March, 1963; Petroski, 1985; Shepherd et al., 2014). Due to this, failure should be seen as an opportunity not as something to be embarrassed of (Cope, 2011; Ewusi-Mensah & Przasnyski, 1995; Shepherd et al., 2013). If the errors are not hidden, but carefully analyzed by the involved individuals, it is possible to prevent future mistakes (Ewusi-Mensah & Przasnyski, 1995). To make this possible, it is important that a positive learning environment with psychological safety should be established in order to enable learning from the failure (Carmeli & Gittell, 2009).

Previous research on learning from failure can be categorized whether learning is considered at the organizational level or at the individual level.

On the organizational level, for instance, Baumard and Starbuck (2005) analyzed 14 failures in a large European telecommunication company. They found that companies, in general, learn little from failures. Either learning does not take place or the wrong things are learned. Research on learning from failure of IT projects is limited. A rare example is Ewusi-Mensah and Przasnyski (1995) that analyzed whether companies learn from failed information systems development projects. They found that most companies do not learn from their failed projects. Another example is Kasi, Keil, Mathiassen, and Pedersen (2008) who analyze the usage of post mortem evaluations after project failures. They find that post mortem evaluations are only seldom conducted due to limited learning capabilities in most IT organizations.

On the individual level, to the best of our knowledge, no study analyzes whether IT professionals learn from failed projects and leverage their knowledge in the future. There is one paper, but it analyzes learning o IT professionals from failure only on a conceptual level (Pflügler, Wiesche, & Krcmar, 2016). There are several studies in management literature that focus on learning from failure (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). These studies analyze professionals from scientific research (Shepherd et al., 2014; Shepherd et al., 2011) as well as entrepreneurs (Shepherd et al., 2013). For instance, they focus on how individuals cope with failure and learn from them (Shepherd et al., 2011) or on the influence of the speed of project termination (Shepherd et al., 2014). However, none of these studies analyzes whether employees can leverage the gained knowledge in future projects or possible failure situations in the future.

This brief overview on the theoretical background of learning from failure shows that there is little research on learning from failure within the IT domain, especially on learning from failure on the individual level. The IT domain is different from other domains. It is characterized by quickly changing developments (Al-Ahmad et al., 2009). Additionally, due to the high failure rate, IT employees quite often face project failure. Therefore, it remains unclear, if project failure still evokes negative emotions and therefore leads to learning or if it is just taken as normal and not considered further. Furthermore, it shows that current literature on learning from failure has not yet analyzed whether it is possible to leverage the gained knowledge in future projects.

Due to these points, it remains unclear whether the results that have been obtained in other domains are transferable to the IT domain and whether the gained knowledge can be leveraged in the future to improve the success of IT projects.

2.2.2 Success of IT projects

There are various dimensions of IT project success. For instance, in software development projects, it is possible to use the number of defects, the deviation from the expected effort or whether the schedule was met (Huckman et al., 2009). Thomas and Fernández (2008) identify three categories of IT project success: project management (On-time, On-budget, Sponsor satisfaction, Steering group satisfaction, Project team satisfaction, Customer/user satisfaction, Stakeholder satisfaction), technical (System implementation, Met requirements, System quality, System use) and business (Business continuity, Met business objectives, Delivery of benefits).

If an external IT vendor is conducting the project, the success of the IT project is mostly determined by the financial performance of the IT project. Previous studies have used the absolute profits of each project (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003), the price of the contract (Gefen et al., 2008) and the profitability of the project (Hoermann et al., 2015; Schermann et al., 2014).

The success of IT projects is a complex construct and is influenced by many different factors (Sauer et al., 2007; Thomas & Fernández, 2008). One important factor that influence the success of the IT project is the team and its members (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999). Each team member has different attributes, such as work history, knowledge, gender or beliefs (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999). The composition of the team influences the performance of the team (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999).

2.2.3 Hypotheses

We argue that project failure triggers learning among IT employees. They develop knowledge about the causes of the failure and about how to react in the future in similar situations. IT employees are normally part of a larger project team. They can leverage the gained knowledge in two ways: first, directly by leveraging the gained knowledge during their work and, second, indirectly by sharing the gained knowledge and experience with other team members. In general, due to knowledge sharing within the team (Deng & Chi, 2015), the whole project profits from knowledge that has been gained by one person that has experienced a failure in the past. Therefore, we formulate the following first hypothesis:

H1: An IT professional that has experienced a failure contributes positively to the success of projects in the future.

If there are more team members who have experienced a failure in the past, we can expect that the performance of the project increase more compared to a team with only a small ratio of team members that experienced a failure. First, it is likely that the reason for failure has been different from team member to team member. Therefore, there should be a broader variety of knowledge within the team. Second, not a single team member that has to pass on the gained knowledge, but several ones can share their experiences. Therefore, there is no bottleneck. Due to this, we formulate the following second hypothesis:

H2: An increased ratio of IT professionals that experienced a failure in the past increases the success of projects.

2.3 Research Method

2.3.1 Data Set

The quantitative data, which is the basis for our analysis, was collected from a German IT service provider. This company generates a large proportion of its revenue with consulting projects and to a minor extent by offering other ITO services such as standard software development and hosting. Due to reasons of confidentiality this company will be named ALPHA. ALPHA granted us full access to their project controlling system, where we were able to extract 36,413 projects that were conducted between January 1995 and April 2014 with detailed metadata, like project revenue, profit, contract type, information on the customer and so forth. Since this data is extracted directly from the system and also used for billing purposes, the quality of the data set is particularly high and not subject to recall bias, which is sometimes mentioned regarding surveys, interviews and case studies (Gefen et al., 2008). Additionally, we were able to gather data of more than 8,000 employees from the internal human resource management system, which enabled us to identify and keep track of employees that were working on these projects. This linkage was especially necessary for observing the individual learning curve of the involved IT professionals.

We filtered the raw data to eliminate internal projects and discarded projects with incomplete data. To remove outliers, we performed a 5% trimming algorithm according to Eriksson (2006) on the variable project performance, which is a common approach in empirical ITO vendor studies (Hoermann et al., 2015; Suarez et al., 2013). The final data set comprised 19,004 projects. To additionally account for the effect of outliers we log-transformed some of our variables (Hair, Anderson, Babin, & Black, 2010).

2.3.2 Variables

The dependent variable of our analysis is the performance of the project. The clients’ project performance can be measured according to the adherence of costs and time estimates, as well as on the quality of project output and realized benefits (Huckman et al., 2009). External service provides measure their performance with a different approach. Studies on vendor’s project performance therefore focus on financial measures, like the price of the contract (Gefen et al., 2008) or the absolute project profits (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003). The metric that we have adapted is *project profitability* (Hoermann et al., 2015; Schermann et al., 2014) due to its relative characteristics that allows the comparison of different sized projects. Due to confidentiality reasons, it has been multiplied with a constant factor. This is a common approach to anonymize profitability (Hoermann et al., 2015; Schermann et al., 2014).

The independent variables in our analysis captures whether there has been experience with failure in the past. We use two different variables for this purpose.

Member with failure experience. We use a binary variable for measuring whether a member of the project has experienced a major failure in the past. The extent of failure needs to be great in order for negative emotions to be generated that will trigger the learning process (Shepherd & Cardon, 2009; Shepherd et al., 2014). We defined major failure based on two criteria. First, the project profitability has to be minus 20% or below. Even if the rate of return may be very low this might not be classified as a failure, if only a small amount of money is involved. Therefore, we chose a minimum loss of 10.000 € as the second criteria. This amount is roughly the revenue an employee generates in one month. Since the values of these conditions are arbitrarily chosen, we conducted robustness checks that confirm our results.

Ratio of Failure Experience. It measures the ratio of project members that have experienced a major failure in the past. The definition of major failure remains unchanged. Accordingly, if the ratio is zero this corresponds to a team where nobody has ever experienced a failure before.

We employ the following control variables in our analysis.

Client Experience within Team. Previous studies have found that client experience has a significant influence on project performance (Ethiraj et al., 2005; Gopal et al., 2003; Lacity & Hirschheim, 1993; Schermann et al., 2014). In general, client experience can be approximated in several ways. It can be measured as a binary variable, where the variable indicates whether there has been prior interaction (Ethiraj et al., 2005; Gopal et al., 2003), as the number of prior projects (Schermann et al., 2014) or as the volume of prior projects (Kalnins & Mayer, 2004). We used the sum of hours worked for that customer within the team.

Project Size. According to Barki et al. (1993) the size of a project has a considerable influence on the risk of the project. Previous studies have found that it significantly increases the project performance (Ethiraj et al., 2005; Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014). In this analysis, project size is approximated by the revenue of the project.

Project Duration. Longer projects are harder to specify and to forecast (Ethiraj et al., 2005; Gefen et al., 2008). It is also more likely that there are changes during the project (Barki et al., 1993; Gefen et al., 2008). Therefore, the performance of long running projects should be lower (Sauer et al., 2007). Project duration has also been included as a variable in other project performance studies (Ethiraj et al., 2005; Gefen et al., 2008; Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014). In this study, project duration is approximated by the number of days that the project ran.

Team Size. A large project team increases the risk of underperformance because of coordination problems (Ethiraj et al., 2005) and therefore it might have a negative influence on the profitability of the project. However, it could also be the case that team size has a positive influence on profitability, if the team is too small and overworked (Ethiraj et al., 2005). Due to its influence, team size has also been used by other studies on project performance (Ethiraj et al., 2005; Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014). In our analysis, team size is defined as the number of different employees that have worked on the project.

Contract type. There are two basic types of IT outsourcing contracts: fixed price (FP) and time & material (TM) (Banerjee & Duflo, 2000; Gopal et al., 2003). In FP contracts, the ITO vendor agrees to deliver a predefined result and gets compensated with a certain fee (Ethiraj et al., 2005). TM contracts are different, because the billing is based on the agreed hourly rate and the working hours that the ITO vendor invested (Ethiraj et al., 2005). The contract type has been used as a control variable by several studies (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014). It is coded as a binary variable, where 0 stands for a TM contract and 1 for a FP contract.

Year of project start. A dummy variable for the year of the project start has been included in the analysis. This variable captures year specific effects such as exchange rate fluctuations, inflation and business fluctuations (Ethiraj et al., 2005; Hoermann et al., 2015).

2.3.3 Data Analysis

Table 10 shows the mean and the standard deviation (SD) of numerical variables and the correlation matrix. In order to reduce skewness, we log-transformed client experience, project size, project duration and team size (Hair et al., 2010).

	Mean	SD	1)	2)	3)	4)	5)	6)	7)	8)
1) Project Profitability	0.31	0.58	1.00							
2) Member With Failure Experience	0.68	0.47	0.01	1.00						
3) Ratio of Failure Experience	0.52	0.42	-0.03	0.85	1.00					
4) Client Experience	15,361	25,132	-0.01	0.41	0.36	1.00				
5) Project Size	96,942	713,951	0.16	0.10	-0.06	0.14	1.00			
6) Project Duration	211	248	0.06	0.20	0.10	0.21	0.59	1.00		
7) Team Size	4.29	6.10	0.11	0.39	0.15	0.39	0.47	0.42	1.00	
8) Contract Type	0.41	0.49	-0.04	0.21	0.24	0.26	-0.15	-0.06	0.13	1.00

Table 10. Descriptive Statistics

To detect multi-collinearity, we employed the variance inflation factor (VIF) (Belsley et al., 1980; James et al., 2013). The values of the VIF lie between 1 and infinity and values between 5 and 10 can be used as a threshold to decide whether a problematic amount of multi-collinearity is present or not (James et al., 2013). We obtained values clearly below 2 and therefore multi-collinearity should not be an issue.

The correlation coefficients between *Client Experience within Team* and the two independent variables as well as between *Member with failure experience* and *Team Size* are moderate, but due to low VIFs should not cause problems.

To test the hypotheses, we construct multiple linear regression models. The first model only contains the control variables. The second model will analyze the first of our two proxies for influence of failure experience, namely *Member with Failure Experience*. The third model analyze the second proxy, *Ratio of Failure Experience*. We have used this approach with two different variables because of robustness reasons.

As our data set contains several projects for the same customer, we have to correct for panel data (Greene, 2003; Wooldridge, 2010). We conducted the Hausman tests for each model to choose between a fixed-effect models and a random-effect model (Maddala & Lahiri, 1992). The test shows that a fixed-effect model should be used in all three models, as the p-values are clearly below 0.05.

2.4 Results

Dependent variable: Project profitability (anonymized)			
Variable	**Base Model**	**Model 1**	**Model 2**
Member with Failure Experience		0.040 *** (0.012)	
Ratio of Failure Experience			0.029 * (0.012)
log(Client Experience)	0.010 *** (0.002)	0.009 *** (0.002)	0.009 *** (0.002)
log(Project Size)	0.066 *** (0.004)	0.066 *** (0.004)	0.066 *** (0.004)
log(Project Duration)	-0.062 *** (0.005)	-0.062 *** (0.005)	-0.062 *** (0.005)
log(Team Size)	-0.151 *** (0.007)	-0.157 *** (0.007)	-0.151 *** (0.007)
Factor(Contract Type)	0.062 *** (0.010)	0.060 *** (0.010)	0.060 *** (0.010)
Factor(Year)	significant	significant	significant
Adj. R-squared	4.68%	4.74%	4.71%
F-value	46.82 ***	45.19 ***	44.87 ***
Hausman test: *Chisq* (*p-value*)	126.60 (< 2.2e-16)	138.07 (< 2.2e-16)	139.87 (< 2.2e-16)
Standard errors are reported in brackets Significance: *** = significant at the 0.1% level; **= significant at the 1% level; *= significant at the 5% level			

Table 11. Results of The Regression Analysis

The results of the multiple regression models are presented in Table 11. First, there is a base model that only contains the control variables.

Model 1 analyzes the first hypothesis *H1: IT professionals that experienced a failure contribute positively to the success of projects in the future.* We find that *Member with Failure Experience* has a positive significant influence on project profitability, which supports the first hypothesis H1.

Model 2 analyzes the second hypothesis *H2: An increased ratio of IT professionals that experienced a failure in the past increases the success of projects.* We find that *Ratio of Failure Experience* has a positive significant influence on project profitability, which supports the first hypothesis H2.

When comparing the coefficients of the control variables between the three models, we find that adding *Member with Failure Experience* and *Ratio of Failure Experience* does not significantly change them. This indicates robust models.

2.5 Discussion

2.5.1 Limitations

All research is subject to limitations. In the following, we discuss possible limitations of our results.

First, our data set comes from only one IT company, which might limit the generalizability of our results. This a general problem when dealing with archival data sets (Gefen et al., 2008; Hoermann et al., 2015; Huckman et al., 2009). Our results could be influenced by to the way ALPHA deals with project failures. However, discussions with representatives of ALPHA revealed that they have no special way of dealing with project failures in comparison with other IT companies.

Second, our definition of failure (a project with less than -20% profitability and a loss of more than 10.000 €) seems arbitrary. We performed robustness checks, where we varied these figures. The drawn conclusion did not differ from the presented ones. Another issue with the employed definition of failure is that it might not be generally possible to tie failure to such numbers. A project that is not complex might already be seen as a failure, if it does not have a positive profitability. However, due to the large number of projects that have been analyzed, such influences should be cancelled out.

Third, although we find significant relationships, the two variables *Member with Failure Experience* and *Ratio of Failure Experience* only slightly increase the adjusted R-squared in comparison to the base model. To address this issue we employed F tests to analyze whether model 1 and model 2 have a significant higher explanatory power in comparison to the base model. We found that both variables (*Member with Failure Experience* and *Ratio of Failure Experience*) significantly increase the explanatory power.

2.5.2 Theoretical and Practical Contribution

We contribute to theory in several ways. First, we reject the results of Ewusi-Mensah and Przasnyski (1995) and Kasi et al. (2008), which are one of the rare studies of learning from failure in the IT domain. Ewusi-Mensah and Przasnyski (1995) analyzed the learning from failed information systems development projects and found that organizations do not learn from them. Kasi et al. (2008) analyzed the usage of post mortem evaluations after project failures and found that post mortem evaluations are only seldom conducted due to limited learning capabilities in most IT organizations. However, we found that IT employees learn from failed project and tend to perform projects that are more successful in the future. A possible explanation for these opposing results could be the different levels of analysis. We analyzed learning on the individual level, but Ewusi-Mensah and Przasnyski (1995) and Kasi et al. (2008) analyzed it on the organizational level. Another possible explanation could be that Ewusi-Mensah and Przasnyski (1995) and Kasi et al. (2008) based their conclusions on the retrospective actions that companies conducted after a failed project. Such actions might be a good way to learn from a failed project, but learning from failure also occurs in an unstructured and informal way among the involved team members.

Second, we extend research on the learning of individuals after a failure to the IT domain. These studies have been conducted in settings like research projects or entrepreneurial activities (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). The IT domain is different than other domains. It is characterized by quickly changing developments (Al-Ahmad et al., 2009). Furthermore, due to the high failure rate, IT employees quite often face project failure (The Standish Group, 2013). Therefore, it remains unclear, if project failure evokes negative emotions among IT employees, which are necessary to trigger the learning process (Shepherd & Cardon, 2009; Shepherd et al., 2014). Our results suggest findings that haven been obtained in other domains (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011) are transferable to the IT domain.

Third, we show that knowledge that has been gained through learning from failed IT projects can be leveraged in future projects and significantly improves the performance. This has not been done in other studies on learning from failure on the individual level (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011; Snell, 1992). This is an important aspect, because having gained knowledge through learning from a failure is one thing, but IT managers are more interested in the question whether future projects perform better because of the gained knowledge.

Fourth, our results show that it already has a positive effect, if only one member of the team has experienced a failure. This member seems to spread its knowledge to other team members which then are able to perform better in certain situations (Deng & Chi, 2015). Additionally, our results show that the higher the ratio of team members with failure experience, the higher the performance of the project. This might be due to the two following reasons. First, it is likely that the reason for failure has been different from team member to team member. Therefore, there should be a broader variety of knowledge within the team. Second, not a single team member that has to pass on the gained knowledge, but several ones can share their experiences, which prevents a bottleneck of knowledge sharing.

We contribute to practice in several ways. First, our results suggest that IT employees that have experienced a failure in the past should be seen as a valuable resource and not as "losers". They should not be devalued or generally blamed for a failure.

Second, IT managers should create an atmosphere for learning for the involved IT professionals after a failed project. Carmeli and Gittell (2009) show that a positive learning environment with psychological safety intensifies learning from failure

Third, our results suggest that it is advisable to staff projects with individuals that have experienced failure in the past in order to increase the project success.

2.5.3 Future Research

We analyze learning from failure on the individual level only indirectly through the performance of future projects. Future research could analyze learning from failure directly based on individual performance indicators.

Another possible direction for future research could be the consideration of the time since the failure occurred. According to Argote, Beckman, and Epple (1990) acquired knowledge gets outdated quickly in organization setting. Therefore, it is likely that the influence of failure experience decreases with time.

Our results show, that it has a positive effect on the project performance, if one team member has experienced a failure in the past. Furthermore, they show that the performance increases, if more team member have a failure experience. Future research could analyze the influence of different configurations of team members with failure experience and team members with no failure experience. We find that the ratio of team members that have experienced a failure in the past significantly increases the performance of a project. Our analysis assumes a linear relationship. Future research could relax this assumption and perform a non-linear analysis. It is possible that the relationship has an inverted U-shape or reaches a plateau after a certain ratio.

Another possible direction for future research could be to analyze whether different types of personalities cope differently with the failure and therefore differ regarding learning from failure (Wiesche & Krcmar, 2014).

Finally, future research could analyze if persons within the social network of an employee that experienced a failure also learn from this failure. Kim and Miner (2007) have analyzed whether organizations learn from failures of other organizations. They found that learning occurs and that it is increased if accessibility to the failure and applicability of the failure to the own business are given.

2.6 Conclusion

This research was motivated by a lack of research on learning from failure of IT employees. We employed a unique data set from a German IT consulting company and found that IT employees learn from failed IT projects and leverage this gained knowledge in future projects. We contribute to theory by extending previous research on learning of individuals in other domains to the IT domain. Furthermore, we contribute to practice by showing that IT employees that have experienced a failure in the past are a valuable resource and should not be blamed or devalued or be seen as “losers”. IT managers should even think about staffing IT projects with employees that have experience with failure.

3. The Dual-Sided Effect of Project Failure on IT Professionals

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Table 12. Fact Sheet Publication P4

Abstract

The effects of project failure on IT professionals have not received much attention in IT research. A failed project evokes negative emotions and therefore could trigger turnover, which has negative influences from the perspective of IT human resource management. However, the failure of IT projects could also have positive influences as professionals might learn from the failed project. This paper focuses on analyzing this dual-sided effect of project failure on IT professionals. We develop hypotheses that will be tested with a large data set from an IT service provider in future research. We expect to contribute to theory by analyzing whether project failure triggers turnover and by analyzing whether IT professionals learn from failed projects and perform better in the future.

3.1 Introduction

IT projects have a quite high failure rate. According to a report by The Standish Group (2013), the rate of unsuccessful projects is higher than 60% and has not significantly decreases over the past decade, although the maturity of the IT market has increased (Pflügler et al., 2015; Schermann et al., 2016). It is estimated that IT project failures create cost of $3 to $6 billion every year (Krigsman, 2012; Sessions, 2009).

Most of the literature on IT project failure has concentrated on identifying factors that lead to failure (e.g. Cerpa and Verner (2009), Keil (1995), Pankratz and Basten (2013), Yeo (2002)). The focus has mostly been on how to prevent it and therefore project failures have been seen as something negative (Grainger, McKay, & Marshall, 2009).

Failed projects not only have a financial impact, but also have negative effects on the project members. They create negative emotions, which could be a shock event that triggers turnover based on the unfolding model of voluntary turnover (Lee & Mitchell, 1994; Shepherd et al., 2013). This relationship has not yet been analyzed. Turnover is problematic for IT organizations, as it is difficult to find a replacement due to the high demand for skilled IT professionals (Streim & Pfisterer, 2014; Thibodeau, 2012). Additionally, turnover creates high costs (Chang, 2010; Sumner & Niederman, 2004; Thatcher et al., 2002).

However, IT research has not yet focused on the possibility that project members might learn from failed projects and leverage these learnings in future projects. Learning on the organizational level has been considered by Ewusi-Mensah and Przasnyski (1995), but they did not focus on individual project members. However, there are studies in management literature that focused on learning from failure on the individual level (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011).

As it can be seen, project failure has a dual-sided effect on IT professionals from the perspective of IT human resource management. On the one hand, it could lead to turnover of IT professionals, which has negative effects, but on the other hand, professionals might learn from the failed project. This has not yet been analyzed in IT literature. Therefore, we pose the following research question:

What is the relationship between project failure and turnover as well as learning from failure on the individual level?

We plan to answer this question with a unique data set from an IT service provider, called ALPHA. They granted us access to data from its internal project controlling and human resource management systems. We gained extensive data on all 36,413 projects conducted by ALPHA between January 1995 and April 2014 and on all 8,180 IT professionals that worked for ALPHA during that time period.

The remaining sections of the paper are structured as follows. First, we present background information on learning from failed projects as well as on turnover of IT professionals. This is followed by the development of the hypotheses that will be analyzed in future research. We then outline our data set in detail und present the planned analysis approach. Finally, the expected contributions are discussed and the paper ends with a conclusion.

3.2 Theoretical Background

3.2.1 Learning from Failure

Project failure can be divided into project management failure, where the project fails to meet cost, time or quality, and into product failure, where the outcome of the project fails to meet the expectations (Baccarini, 1999; Pankratz & Basten, 2013; The Standish Group, 2013). As previously mentioned, quite a significant share of IT projects fail which creates high costs (Krigsman, 2012; Sessions, 2009; The Standish Group, 2013).

Most of the literature on IT project failure has concentrated on identifying factors that lead to failure (e.g. Cerpa and Verner (2009), Keil (1995), Pankratz and Basten (2013), Yeo (2002)). This focus on hindering project failure creates a negative view. However, a failure might not always be a total loss and offers the opportunity to learn from it (Ewusi-Mensah & Przasnyski, 1995; Grainger et al., 2009).

For instance, Ewusi-Mensah and Przasnyski (1995) argue that organizations should keep record of their failed projects and try to understand what went wrong. According to Grainger et al. (2009), project failures should be considered in a broader context, as the learning from a failure could be the reason for a subsequent successful project. However, the mentioned studies focus on the organizational level and did not consider the learning from project failure on the individual level.

Learning from failure on an individual level has been analyzed in management literature (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). It has been found that failure evokes negative emotions, but depending on how individuals cope with these emotions leads to learning (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). Members of the failed project start thinking about different actions that could have been taken and their influence on the project (Shepherd et al., 2011). By doing so they develop capabilities and knowledge about how to react in similar situations in future projects (Eisenhardt & Martin, 2000; Shepherd et al., 2011).

3.2.2 Turnover of IT professionals – The Unfolding Model of Voluntary Turnover

Turnover is defined as "voluntarily leaving an IT job for an alternative IT job with a different employer" (Joseph et al., 2015). Turnover is problematic for IT organizations, as it is difficult to find a replacement due to the high demand in the IT labor market (Streim & Pfisterer, 2014; Thibodeau, 2012). Additionally, turnover creates high costs through recruiting and training, but also through the disruption of organizational processes (Chang, 2010; Sumner & Niederman, 2004; Thatcher et al., 2002). There are several studies that estimate these costs to be between 90% and 700% of the annual salary of an IT professional (Allen et al., 2010; Kochanski & Ledford, 2001).

The unfolding model of voluntary turnover after Lee and Mitchell (1994) is a theory that has gotten more popular in recent turnover research (Allen et al., 2014). It focuses on the decision process of turnover and argues that a shock event often acts as a trigger. Shock events can either be (1) positive or negative, (2) expected or unexpected and (3) originate on the organizational or personal level (Lee et al., 1999). Several decision paths that can be taken by IT professionals have been proposed by Lee and Mitchell (1994).

This kind of turnover theory has been mentioned by several IT as well as general turnover related literature reviews as a possible area for future research (Allen et al., 2014; Holtom et al., 2008; Joseph et al., 2007). According to Joseph et al. (2007) IT turnover research should focus on understanding events that trigger turnover.

Recent IT turnover literature has employed and contributed to the unfolding model of voluntary turnover. Niederman et al. (2007) have found additional decision paths that are especially relevant to the IT domain. Mourmant and Gallivan (2007) focused on the influence of personality on taking different decision paths. There are a few studies that employed the unfolding model of voluntary turnover to analyze the turnover of IT professionals that have the aim of founding an own company (Mourmant et al., 2009; Mourmant & Voutsina, 2010, 2012).

3.3 Hypotheses

The aim of this article is to examine the dual-sided effect of project failure on IT professionals.

A project failure could be a shock event after the unfolding model of voluntary turnover of Lee and Mitchell (1994). It has been shown that project failures evoke negative emotions, such as frustration, disappointment, depression, anger or doubts about one's work (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). These emotions should be strong enough to trigger the decision processes of turnover. Employing the categorization of Lee and Mitchell (1994), a project failure is a shock that is (1) seen negatively by the individual, (2) mostly unexpected, as individuals normally do not expect the failure at project start, and (3) originates on the organizational level. Therefore we formulate the following hypothesis:

H1: Project failure increases the probability of turnover among the members of the team that worked on the project.

A project failure enables members of the project to learn from the failure to improve their knowledge for future projects (Ewusi-Mensah & Przasnyski, 1995; Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). It has even been claimed that the possibility to learn from failure is higher than from success (Petroski, 1985; Popper, 1959). The reason for this is that a success does not attract enough attention to think about the causes for this positive outcome (Eisenhardt & Martin, 2000). Project members of a failed project can leverage their gained knowledge and tend to conduct on average more successful projects regarding budget, time and quality in the future (Shepherd et al., 2011). Therefore, the following second hypothesis is formulated:

H2: Team members that have experienced a project failure conduct more successful projects in the future.

3.4 Method

3.4.1 Data Sample

In order to examine these hypotheses, we extracted data from the internal project controlling and human resource management systems of a large German IT service provider, which is called ALPHA due to non-disclosure reasons. Directly accessing quantitative data from internal systems is not subject to recall bias, which could be a problem in case studies and surveys (Gefen et al., 2008; Josefek & Kauffman, 2003). ALPHA granted us access to all 36,413 projects conducted between January 1995 and April 2014. Additionally, we collected information on all of its 8,180 IT professionals that worked during that time period for ALPHA.

We collected information about each project such as the project profitability, the contract type, the team size, the number of interactions with a client as well as within an industry, the business climate based on a recognized index, the project start, the project size, the industry of the client and the project duration. To link each IT professional to the projects, we extracted the information which professional worked how many hours for which project on which day. Detailed Information about the yearly performance review, the planned and attended trainings, the home base, the educational background, the organizational unit, the job level, the recruitment date and the turnover date of the IT professionals have as well been collected.

3.4.2 Measures and Planned Data Analysis

For analyzing the described hypotheses, we created subsets of the previously described overall data set. The measures of these subsets are described in Table 13 and Table 14. We plan to analyze the hypotheses H1 and H2 with the two described subsets. As turnover is a dichotomous variable, H1 will be analyzed with a logistic regression model. H2 will be analyzed with an ordinary least squared regression model.

Dependent variable	• **Turnover**: This information has been directly extracted from the human resource management systems and therefore allows the analysis of actually occurred turnover, which is an under-researched area (Joseph et al., 2007; Lo, 2015).
Independent variables	• **Project failure experienced**: Projects with a high negative profitability and a certain amount of loss are used as a proxy for this measure, because they can be seen as a failure for ALPHA. This measure captures whether team members have experienced a project failure in the past. • **Control variables**: Several factors that have been found to influence turnover are employed as control variables, such as age, gender, organizational tenure, training and educational background (Joseph et al., 2007; Lo, 2015).

Table 13. Measures for analyzing H1

Dependent variable	• **Project profitability**: This measure has been extracted from the project controlling systems of ALPHA.
Independent variables	• **Project failure experienced:** Projects with a high negative profitability and a certain amount of loss are used as a proxy for this measure, because they can be seen as a failure for ALPHA. This measure captures whether team members have experienced a project failure in the past. • **Control variables**: Research on ITO vendor profitability has revealed several factors that have an influence on profitability, such as project size, duration, team size, client knowledge, industry knowledge (Hoermann et al., 2015; Schermann et al., 2014)

Table 14. Measures for analyzing H2

3.5 Expected Contribution

According to Joseph et al. (2007) the unfolding model of voluntary turnover and the identification of shock events has not yet received much attention in IT turnover literature. In recent years, it has gotten more popular and has been employed by several studies (Mourmant & Gallivan, 2007; Mourmant et al., 2009; Mourmant & Voutsina, 2010, 2012; Niederman et al., 2007), but they did not focus on project failure as a possible shock event.

An expected practical contribution is that project failure could trigger turnover and that IT managers should intervene to prevent the turnover of key IT professionals. It has been shown, that retention actions should be taken rather quickly, because professionals that experienced a shock tend to leave faster than professionals with a low satisfaction (Lee et al., 1999).

Another theoretical contribution will be the understanding of project failure as a learning opportunity for IT professionals. This has not received much attention in IT literature. We expect to shed light into the relationship between project failure and learning from this failure of IT professionals.

IT professionals should be carefully selected for risky projects. Professionals that already have a low organizational commitment and high levels of stress could be indirectly forced into turnover. Additionally, learning from failure should not always be experienced by the same people, because otherwise they do not have the opportunity to exploit their learnings in less riskier projects.

After analyzing the described hypotheses, future research could analyze the underlying relationships in more detail. This could be done with explorative qualitative studies. An interesting research topic could be to analyze how employees could learn from project failures without having to be a member of the failed project. Additionally, the personality of the IT professionals could be taken into account, which has been found to significantly influence job outcomes (Clark, Walz, & Wynekoop, 2003; Hall, Cegielski, & Wade, 2006; Wiesche & Krcmar, 2014). Shepherd et al. (2013) suggest that employees differently cope with failures.

3.6 Conclusion

Project failure has mostly been considered as a negative event in IT literature. We extend this view and argue that failure could have a dual-sided effect. It should increase the probability of turnover among the members of the project, but on the other hand the project members have the opportunity to learn from the failure and increase their contribution to the performance of future projects. We expect to shed light into these relationships through the outlined future research.

4. Strategies for Retaining Key IT Professionals[2]

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Table 15. Fact Sheet Publication P6

Abstract

Retaining IT professionals is a key and challenging issue for IT managers. There is no "silver bullet" and retention actions must be tailored to the profile of each employee the organization wants to retain. IT professionals have different reasons for changing jobs, determined by their career goals, relationships within the organization and current attitude to the job. We show how IT employees can be classified into seven types and describe the retention actions that will work best for each type.

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4.1 Retaining IT Professionals is a Key Issue for IT Managers

Turnover of IT professionals poses several challenges to IT organizations. First, finding a successor to someone who has quit is often difficult due to the high demand for skilled IT professionals in the global IT labor market. As IT managers are well aware, programming is one of the most sought after professions (Torpey, 2016). Moreover, high demand for skilled and specialized IT professionals is predicted to continue to increase in the future (Strauss, 2017).

Second, it is not only difficult but costly to find a skilled replacement for a professional who has quit. Turnover creates direct costs, such as recruiting and training, as well as indirect costs through the disruption of organizational processes. Studies have estimated these costs to be between 90% and 700% of the annual salary of the replacement IT professional (Allen et al., 2010; Kochanski & Ledford, 2001). One reason for such high costs is the time it takes for a new IT professional to become fully productive, which one study estimated to be around 18 months (Baroudi, 1985). Because IT professionals are a scarce resource and their turnover is costly, IT managers should focus on reducing turnover and retaining existing employees.

Generally, the retention process evolves as follows. Weak signals sent by an employee or the work environment provide clues to the IT manager that there is a probability of an IT employee quitting. If the probability of leaving is above a certain level, the manager can decide whether to make an effort to retain the employee; it may not be cost-effective or prudent to retain every employee who wants to leave. Some potential leavers might just not fit or might be detrimental to the overall "good" of the organization if they remain. However, if the IT manager deems that the employee is a valuable asset to the organization, he or she is duty bound to take appropriate retention actions to prevent the employee leaving.

Choosing the best actions to retain an IT professional who is considering leaving is not straightforward. Cost and time restrictions may preclude using all possible retention actions, and individuals respond differently to the various actions. For example, the employee's current stage of career development might influence his or her reaction to retention actions: younger employees with less experience are often more interested in climbing the career ladder, whereas more seasoned or older professionals might be more focused on achieving a work-life balance to spend more time with family or on hobbies. Furthermore, employees have different motivations for working for their current employer and these will influence the effectiveness of retention actions. Other factors potentially affecting an employee's a reaction to retention actions include relationships with co-workers and attitude to the current job situation.

This article reports the findings of a study that sought to understand the process for retaining IT professionals, focusing on different types of IT employees and corresponding retention actions. We surveyed 283 employee exits of a large German IT service provider and from the analysis of the survey data clustered them into seven types of IT professionals, according to their original motivation for joining the business, their relationships within the company and their reasons for leaving. Next, we identified the best retention actions for each type of leaver based on information from the survey and interviews with IT managers at the service provider. (The research method is described in the Appendix.)

The seven types of IT leavers and the corresponding retention actions will help IT managers to choose the best options when they become aware that a valued IT employee is considering leaving and thus increase the chances of retaining that employee.

4.2 Actions for Retaining IT Employees

IT managers can take various retention actions to persuade an employee to stay with the firm, but because these actions can have different effects, choosing the most effective one is difficult. According to one IT manager we interviewed, it is possible to retain about every second IT employee who is considering leaving, but only if the right retention actions are chosen.

Prior studies and practitioner interviews suggest that the following five actions can help to retain IT employees (Agarwal et al., 2006; Agarwal & Ferratt, 1998; Bairi, Murali Manohar, & Kundu, 2011; Joseph et al., 2015; Thomas, 2015).

1. Financial or Non-financial Compensation. In general, IT employee compensation is influenced by organizational, industry-related and national factors, individual and job-level factors, and strategic decision factors (Wang & Kaarst-Brown, 2014). Financial compensation, such as a pay raise or a bonus, is likely to increase job satisfaction and may be perceived as a form of appreciation (Agarwal et al., 2006; Joseph et al., 2015). However, financial compensation might not be an effective way of retaining IT professionals because they are generally well-paid (at least in the U.S. and most European countries) (Bureau of Labor Statistics, 2017). Non-financial compensation, such as motivational feedback or team building events, also influence retention (Agarwal & Ferratt, 1998) and can be a cost-effective way of retaining employees. Fortunately, this type of compensation requires minimal effort to implement on the part of the IT manager.

2. Working Arrangements. Special working arrangements may help to retain an IT employee (Agarwal & Ferratt, 1998; Niederman et al., 2007). These arrangements include office workspace, the work location of the employee, the possibility of working from home and flexible working hours (Agarwal & Ferratt, 1998). Working from home is quite common among IT employees (Bureau of Labor Statistics, 2016). In general the nature of IT work and the availability of modern communication and collaboration tools make it possible to implement alternative working arrangements for IT employees.

3. Career Development Opportunities. Career development is an important issue for many IT professionals. Promotion is an obvious way to advance an IT employee's career (Agarwal & Ferratt, 1998), but providing training can be used to achieve the same end (Agarwal et al., 2006). IT employees' knowledge and skills can rapidly go out of date, leading to professional obsolescence, and training programs are a means of counteracting technical obsolescence (Joseph & Ang, 2010). Laying out a long-term career plan for an IT employee can direct career development. Outlining the requirements for achieving the next level of career development can support the employee in achieving career goals and decrease any uncertainty the employee might be experiencing about her or his future at the organization. Empirical findings suggest that career development for IT professionals could mean moving them to non-IT positions in the organization (Reich & Kaarst-Brown, 1999, 2003).

4. Change of Department. Relationships with co-workers and supervisors can influence retention rates (Agarwal et al., 2006; Agarwal & Ferratt, 1998). If these relationships are poor or unsatisfactory, assigning an IT employee to a different department within the IT organization with a different supervisor can provide the employee with the opportunity to make a fresh start. The project-oriented nature of IT work makes it relatively easy to switch an employee to a different department.

5. Varying Work Tasks. Performing the same or similar tasks repetitively over an extended period can lead to boredom and possibly hinder an IT employee from reaching his or her full potential. Providing an opportunity to work on a new and challenging task can be motivating (Niederman et al., 2007). However, what constitutes a challenging task may be different for each IT professional. Some might focus more on technical aspects, like working with a new technology, whereas others might be more interested in and challenged by working in a new domain.

4.3 Challenges of Configuring Retention Actions

Finding the right combination of retention actions for IT professionals that IT managers want to keep is challenging. Cost and time restrictions mean it may not be possible to simply try out all the actions to test which of them works. Retention actions incur costs, especially improving financial compensation and providing additional training. Alternative working arrangements, a change in department and assignment to new tasks are also potentially costly because it might not be possible to deploy the IT professional in the most productive way. Although providing career development opportunities through promotion and non-financial compensation are the least costly retention actions, their effectiveness in reducing turnover is uncertain and they involve some administrative overhead costs.

Moreover, retention actions take time to be effective. When IT managers perceive there is a high probability that an employee will leave, they should implement the most promising retention action first. One of our interviewees highlighted the difficulty of selecting the right retention action:

> *"The employee actively expressed his dissatisfaction about his current job situation in the yearly performance review. After receiving his notice [to quit], I offered him a promotion, but he did not accept it. Later on, I found out that it was more the tasks he was assigned to than the job level that influenced his decision, but it was too late to convince him to stay. After receiving a notice [to quit], you have to respond quickly."* IT Manager

The combination of retention actions needs to be tailored for each IT professional that IT managers want to keep. Each IT employee has different motivations and sets individual goals to achieve during their employment. If employees feel they can no longer reach their goals, they are more likely to consider moving to another company. Retention actions should therefore consider the reasons why an IT professional chose to work for the company in the first place. The choice of retention actions is also influenced by an individual's relationships with co-workers and supervisor (Agarwal et al., 2006; Agarwal & Ferratt, 1998). Most IT work is conducted in teams where the outcome depends on close collaboration between team members

(Vidgen & Wang, 2009). The employee's attitude to the job situation should also be considered when choosing appropriate retention actions. Attitude is a proxy for job satisfaction, which researchers have found is an antecedent of an intention to leave the firm (Joseph et al., 2007).

A good working relationship between IT manager and IT employee will help the manager to understand the employee's motivation for joining in the first place, the "fit" of the employee to the organization, and the employee's attitude to the job and current projects or tasks. A close relationship will also help the manager to assess if the employee is considering leaving. According to an IT manager we interviewed, close relationships with employees makes it possible to identify roughly 50% to 70% of those who are thinking about leaving. Establishing a close relationship, however, is not always easy. For example, establishing a good working relationship may be difficult if the IT manager and employee are not co-located. The lack of proximity may prohibit direct observations of the employee's behavior during a daily meeting or verbal (and non-verbal) interactions with colleagues.

IT managers should also consider the current organizational context when deciding which retention actions to apply. Assigning an employee to a new department is only possible if a department is willing and able to offer a position. Moreover, retention actions differ in terms of how easy they are to implement and how long they remain effective. Improving financial compensation, for example, is easier to action than creating special working arrangements that meets the employee's unique private-life demands, but financial rewards might not remove the reason for the employee's dissatisfaction.

4.4 Seven Types of IT Leavers and Possible Retention Strategies

From our analysis of the survey conducted among former employees of the German IT service provider, and from interviews with IT managers at the provider, we have classified these IT leavers into seven types of IT employees. Our classification is based on employees' original motivations for joining the firm because we see this as a proxy for career goals and employee relationships within the organization because IT work is mostly conducted in teams. We believe these two factors are important determinants of job satisfaction, which is an important determinant of turnover. The classification is also based on the reasons given for leaving the organization.

The seven types are summarized in Table 16, which for each type lists the motivations for originally joining, the state of the relationships between the leaver and his or her co-workers and supervisor, and the reasons for leaving.

Leaver Type	Original Joining Motivation	Relationships[3]	Reasons for Leaving
A: "I Have No Real Stock Here"	• Recommendation from friend/colleague	• Average relationship with co-workers • Slightly poorer relationship with supervisor	• Insufficient non-monetary recognition • Lack of career opportunities • Dissatisfaction with general work environment • External job offer
B: "This Is the Wrong Job for Me"	• Opportunity to work on challenging tasks • Size and location of company	• Average relationship with co-workers • Good relationship with supervisor	• Dissatisfaction with general work environment • Lack of career opportunities • Poor fit between employee and assigned task
C: "The Job Does Not fit with My Spouse or Partner's Needs"	• Recommendation from friend/colleague • Size and location of company	• Very good relationship with co-workers and supervisor	• Dissatisfaction with work-life balance • Dissatisfaction with general working environment • Personal triggers related to private life
D: "I Do Not Like It Here"	• Recommendation from friend/colleague • Company culture • Size and location of company	• Very poor relationships with co-workers and supervisor	• Poor working relationship with supervisor • Insufficient non-monetary recognition • Dissatisfaction with general working environment • Lack of career opportunities • Dissatisfaction with work-life balance
E: "I Need Something New"	• Recommendation from friend/colleague • Opportunity to work on challenging tasks • Company culture • Career advancement	• Very good relationships with co-workers and supervisor	• Lack of career opportunities • Dissatisfaction with work-life balance • Desire for new/challenging tasks and topics
F: "I Lack Career Development Opportunities"	• Opportunity to work on challenging tasks • Recommendation from friend/colleague • Size and location of company • Career advancement	• Average relationship with co-workers • Very poor relationship with supervisor	• Lack of career opportunities • Poor working relationship with supervisor • Dissatisfaction with general working environment • Insufficient non-monetary recognition • Lack of personal development and poor social interactions
G: "I Just Don't Fit Here Anymore"	• Opportunity to work on challenging tasks • Size and location of company • Company culture • Career advancement	• Average relationship with co-workers and supervisor	• Various reasons

Table 16: Seven Types of IT Leavers

Below, we suggest retention strategies that could have been applied to each of these types of leavers and a process for implementing the retention actions. These actions are intended to support IT managers in the retention of IT professionals and, as a result, reduce—or even prevent—IT employee turnover.

[3] Relationships for each type were assessed against the average rating of relationships across all survey respondents.

4.4.1 Type A IT Leavers: “I have No Real Stock Here“

Summary. This type of IT leaver joined the organization because of a recommendation from a friend or previous colleague. The relationship with co-workers was average, but slightly poorer with the supervisor. This type of leaver gave four main reasons for moving on: insufficient non-monetary recognition for achievements/contributions, a lack of career opportunities, dissatisfaction with the general working environment and a job offer from another company. On average, this type of IT employee stays in their job for nearly 2,000 days (Table 17)—about a year longer than the other types.

Average tenure (days)	1,990
Previously considered leaving	20%
Turnover was preventable	60%
Talked first to supervisor about intention to leave	40%
Reasons for joining the organization	Recommendation from friend/colleague (85%)
Reasons for leaving	Insufficient non-monetary recognition (65%)
	Lack of career opportunities (55%)
	Dissatisfaction with general work environment (25%)
	External job offer (response to open question)

Table 17: Characteristics of Type A IT Leavers

Indicators for Type A Leavers. The main indicator that this type of IT employee may be considering leaving is that, although they are not dissatisfied, they are not particularly happy with their work situation. Another indicator is that they have worked for the company for quite a while. A possible third indicator is that they have a slightly poorer relationship with their supervisor than their peers.

Type A leavers feel they have not received appropriate or sufficient recognition for work performed. They do not foresee future career opportunities with their current employer, possibly as a result of the poorer relationship with the supervisor. As the overall situation of Type A leavers is not particularly bad, they often do not quit on their own accord. Rather, external events, such as a job offer, finally convince them to hand in their notice to leave. Turnover among Type A IT employees is difficult to anticipate because they do not communicate their dissatisfaction. From an IT manager’s perspective, there is little warning until an apparently minor incident convinces them to leave.

Retention Actions. 60% of Type A leavers, compared to 53% of the six other types, stated that they could have been persuaded to stay: 45% of these said they would have stayed if they had received a pay raise, 30% would have stayed if they had been offered new career opportunities/challenges and 20% would have reversed the decision to leave if they had been assigned to a different supervisor.

The best retention action for a Type A IT employee is to initiate informal conversations with the aim of building trust and providing the employee with the feeling that the IT manager cares about her or him.

> *"You have to regularly talk with [Type A IT employees], but in an informal way. ... The conversation should be about their job satisfaction, career possibilities and about areas in which they can improve; not too direct but in an honest way."* IT Manager

Having identified a person that as a Type A IT employee, it might be advisable not to expose her or him to an external event such as attending a conference. Instead, the IT manager should carefully examine the employee's preferences and provide transparent career options.

4.4.2 Type B IT Leavers: "This Is the Wrong Job for Me"

Summary. The primary original motivation for Type B leavers to join the company was that they wanted to work on challenging tasks. In general, Type B employees have a normal relationship with their co-workers and get along well with their supervisor. The main reasons given by this type of IT employee for leaving are a poor fit with the assigned task, dissatisfaction with the general working environment and a lack of career opportunities (see Table 18).

Average tenure (days)	960
Previously considered leaving	31%
Turnover was preventable	81%
Talked first to supervisor about intention to leave	56%
Reasons for joining the organization	Opportunity to work on challenging tasks (62.5%)
	Size and location of company (25%)
Reasons for leaving	Dissatisfaction with general working environment (93.8%)
	Lack of career opportunities (31.2%)
	Poor fit between employee and assigned task (response to open question)

Table 18: Characteristics Type B IT Leavers

Indicators for Type B Leavers. Type B IT employees originally joined the company because of an opportunity to tackle challenging tasks but then become dissatisfied with these tasks and the general working environment. This causes an imbalance between personal expectations and the reality of the job. Despite their dissatisfaction with their current work, Type Bs have good relationships, especially with their supervisor. This good relationship opens the door for IT managers to talk openly with Type B employees about current tasks and their goals within the organization. The shorter average tenure of this type of leaver (960 days) suggests that they realized early on that either the job or the task did not match their expectations.

Retention Actions. At 81%, the proportion of Type B leavers who stated that they could have been prevented from leaving is larger than that of the other types (about 53%). Because this type of IT employee has good relationships with colleagues, their dissatisfaction with the general working environment is mainly related to dissatisfaction with the assigned tasks and a lack of career opportunities. This implies that turnover among Type B IT employees is primarily related to the way they are managed and could have been prevented. One of our interviewees said that his company had identified the link between incorrectly assigned IT employees and increased turnover. In response, new job openings are now advertised internally as well as externally.

> *"We now have the possibility of internal application. Job offers are promoted internally and employees may apply for those jobs. ... We expect that our executives don't cling to their subordinates—those who want to work somewhere else ... leave the company. Ideally it's better if they stay in the company but work on a different job."* IT Manager

Other important retention actions for Type B IT employees is providing career development opportunities and finding more suitable tasks. However, finding the right or new tasks immediately might not be possible. The IT manager should re-assure the employee that her or his wishes have been noted and assignment to a new task will be accomplished as soon as possible.

4.4.3 Type C IT Leavers: "The Job Does Not Fit with My Spouse or Partner's Needs"

Summary. Type C IT employees often join the organization because of a recommendation from a friend or because of the organization's size and location. They have a very good relationship with colleagues and gets along well with their supervisor. Together with Type E IT Employees ("I Need Something New"), Type Cs have the best relationships within the organization of all the seven types. Their reasons for leaving are to do with personal/private issues and because of an unsatisfactory work-life balance. For example, their job may involve too much travel, their commute is too long or their partner lives in another city. This type of IT leaver mentioned a variety of private/personal triggers for leaving, some of which related to the needs of the spouse or partner (see Table 19). However, none of these triggers can be controlled or changed by the company.

Average tenure (days)	1,600
Previously considered leaving	16%
Turnover was preventable	27%
Talked first to supervisor about intention to leave	65%
Reasons for joining the organization	Recommendation from friend/colleague (84%)
	Size and the location of company (29.7%)
Reasons for leaving	Dissatisfaction with work-life balance (27%)
	Dissatisfaction with general work environment (24.3%)
	Different personal triggers, most of which are related to private life
	Relocation is a frequently reported trigger (response to open question)

Table 19: Characteristics of Type C IT Leavers

Indicators for Type C Leavers. Because the triggers for leaving are based on the employee's private life, it may not be easy for IT managers to identify potential Type C IT leavers. However, conversations about their private lives might help managers to identify Type Cs. In general, indicators for Type C IT leavers are changes or events in their private lives such as getting married or becoming a parent.

The proportion of Type C leavers who had previously considered leaving is just 16%, the lowest of all seven types. Type C IT employees seem to be loyal to their company and satisfied with their current work situation.

Retention Actions. The majority of Type C leavers (73%) stated that they could not have been prevented from leaving the company. Turnover caused by private issues is very difficult to prevent.

> *"... you can say what you want [to Type C employees]—it doesn't change a thing. Even if you manage to change his mind, the urge will remain and sooner or later he will eventually leave."* IT Manager

Possible retention actions might be to create special working arrangements that would improve the employee's work-life balance or to offer a job at another of the organization's locations. However, these actions would only be effective if they addressed the private trigger.

> *"If [an employee comes to me and says] 'My partner has received a great job offer somewhere else and therefore I am leaving,' then I think that the company can do something. For example, [it could] offer some kind of dual career service, which aims to support dual-career couples."* IT Manager

Personalized retention actions require substantial effort on the part of the IT manager and perhaps even by company administration, but can lead to increased loyalty in the longer term. IT managers might therefore consider initiating them only for employees with high value to the company or department. If it is not possible to prevent a Type C IT employee from leaving, it is important to communicate that he or she is welcome to return should the personal situation change.

4.4.4 Type D IT Leavers: "I Do Not Like It Here"

Average tenure (days)	1,690
Previously considered leaving	50%
Turnover was preventable	72%
Talked first to supervisor about intention to leave	44%
Reasons for joining the organization	Recommendation from friend/colleague (61.1%)
	Company culture (33.3%)
	Size and the location of the employer (27.8%)
Reasons for leaving	Supervisor (55.6%)
	Insufficient non-monetary recognition (33.3%)
	Dissatisfaction with general working climate (27.8%)
	Lack of career opportunities (22.2%)
	Dissatisfaction with work-life balance (22.2%)

Table 20: Characteristics Type D IT Leavers

Summary. Type D IT employees originally joined the organization because of a recommendation from a friend or colleague, or because of the company culture, size or location. Despite initial enthusiasm, Type Ds seem unhappy with their current situation. Their relationships with their supervisor and with their co-workers are poor. In comparison to the other six types, poor social relationships seem to be the dominant factor for their dissatisfaction. In general, Type D IT leavers mention a broad variety of reasons for leaving, including their supervisor, a lack of non-monetary recognition, the general working climate, lack of career opportunities and work-life balance (see Table 20).

Indicators for Type D Leavers. Because Type D IT employees have poor relationships within the company, it might not be easy to identify potential leavers of this type. The main indicator for Type D IT leavers is that they express dissatisfaction with nearly everything.

Retention Actions. Although unhappiness with the work situation might be difficult to rectify, 72% of Type D leavers stated that they could have been prevented from leaving. However, it is hard to see how an IT manager could convince a Type D employee to stay with the company. In fact, the best action might be to let the individual leave. Unhappiness with the current job and company might be a source of negativity and spread within the team.

> *"A dissatisfied employee can be the infamous 'rotten apple.' When you mix a rotten apple with five healthy ones, two or three others are infected. You really have to be careful."*
> IT Manager

However, if the employee is a valuable resource and it makes sense to initiate efforts to retain her or him, a change of department might be the most promising approach. This could offer the employee an opportunity to start over with new co-workers, a new supervisor and possibly new projects.

4.4.5 Type E IT Leavers: "I Need Something New"

Average tenure (days)	2,210
Previously considered leaving	35%
Turnover was preventable	52%
Talked first to supervisor about intention to leave	70%
Reasons for joining the organization	Recommendation from friend/colleague (87%)
	Opportunity to work on challenging tasks (39.1%)
	Company culture (21.7%)
	Career advancement (21.75)
Reasons for leaving	Lack of career opportunities (30.4%)
	Work-life balance (26.1%)
	Desire to work on different tasks and projects (response to open question)

Table 21: Characteristics Type E IT Leavers

Summary. With an average tenure of 2,210 days, Type E IT employees stay with the company the longest. They originally joined the organization because of a recommendation, the prospect of challenging tasks, the company culture and the opportunity to advance their careers. Type Es have very good relationships with co-workers and their supervisor. The main reasons they give for leaving are the lack of career opportunities and dissatisfaction with work-life balance.

Other triggers for leaving mentioned by Type Es are related to their desire to work on new tasks and new projects (see Table 21).

Indicators for Type E Leavers. Many Type E characteristics are similar to those for Type C ("The Job Does Not Fit with my Spouse or Partner's Needs"). However, the main triggers for a Type C IT employee leaving are to do with personal/private issues, whereas the main reasons for Type E employees leaving are related to their career and the job. Another difference between these two types is that 52% of Type E leavers stated that their departure could have been prevented, whereas only 16% of Type C leavers could have been persuaded to stay at the organization.

Retention Actions. The average tenure of Type E IT employees is nearly seven years, during which they may well have been performing similar tasks and may therefore have become bored with their job. IT managers can prevent Type E employees from leaving by offering them new projects and new career opportunities. However, these retention actions will be successful only if the individual plans to stay in the IT profession and if the company can offer topic-related training. Retaining an IT employee seeking a change of career may be difficult. The best option might be for the IT manager to assure the individual that she or he is welcome to return if things do not work out.

> *"There are employees who say: 'Everything is OK here, but now I need to see something new.' And that's alright. The only thing you can do is to bid them farewell and say: 'If you get tired after three years, you are welcome to come back to us. ... The doors are open.'"* IT Manager

4.4.6 Type F IT Leavers: "I Lack Career Development Opportunities"

Average tenure (days)	1,580
Previously considered leaving intent	20%
Turnover was preventable	72%
Talked first to supervisor about intention to leave	56%
Reasons for joining the organization	Opportunity to work on challenging tasks (72%)
	Recommendation from friend/colleague (44%)
	Size and location of the company (40%)
	Career advancement (36%)
Reasons for leaving	Lack of career opportunities (52%)
	Supervisor (32%)
	Dissatisfaction with general working environment (32%)
	Insufficient non-monetary recognition (24%)
	Personal development and poor social interactions (response to open question)

Table 22: Characteristics of Type F IT Leavers

Summary. Type F leavers originally joined the organization because they wanted to work on challenging tasks, a friend or colleague recommended the organization, they liked the location of the company, or they were looking for career advancement. All aspects of Type F's relationships within the organization are rated lower than average. The relationship between Type F employees and the supervisor is particularly poor. The most frequently mentioned trigger for leaving is a lack of career opportunities, followed by the supervisor, the general working environment and a lack of non-monetary recognition. Personal development and poor social interactions were frequently mentioned in the responses to open questions as triggers for leaving (see Table 22).

Indicators for Type F Leavers. The main characteristic of Type F IT employees is the poor relationship with the supervisor and demand for career opportunities. Type Fs do not feel valued and might feel blocked in their career by their current work situation. They joined the organization hoping to work on challenging tasks, but feel they cannot achieve their goals.

Retention Actions. The majority of Type F leavers (72%) stated that they could have been have been prevented from leaving. To retain a Type F employee, IT managers should first evaluate whether the perceived block in career advancement is real or if the employee has a false impression. Assessing the validity of this perception might reveal that the employee is not of value to the department or company, and the best action might be to let the employee leave.

Offering new career opportunities, a change in supervisor or the chance to apply for internal positions might aid in retaining Type F IT employees.

> *"We had this very competent employee who aimed at becoming head of department. However, we had chosen someone external for this position. He was very disappointed and after a year, suddenly, he joined one of our main customers. ... [His departure] was our fault. We should have given him another career perspective after the [new] head of department blocked his way."* IT Manager

Several of the IT managers we interviewed reported that their organizations had introduced the "strengthening strengths" approach, which aims to help employees identify their strengths and plan their career progress accordingly. This approach might be an effective action for retaining Type F IT employees.

4.4.7 Type G IT Leavers: "I Just Don't Fit Here Anymore"

Summary. Type G leavers mentioned several different reasons for originally joining the organization. The most frequent were challenging tasks, the size and location of the company, and company culture. Type Gs have an average relationship with their co-workers and their supervisor. They also mentioned several different reasons for leaving, the most frequent being dissatisfaction with the available career opportunities and inadequate work-life balance (see Table 23).

Average tenure (days)	1,570
Previously considered leaving	25%
Turnover was preventable	50%
Talked first to supervisor about intention to leave	58%
Reasons for joining the organization	Opportunity to work on challenging tasks (55.6%)
	Size and location of company (49.3%)
	Company culture (31.2%)
	Career advancement (22.9%)
Reasons for leaving	Lack of career opportunities (34.7%)
	Work-life balance (25.7%)
	A broad variety of reasons concerned with private life, salary and dissatisfaction with the current project and job (answers to open question)

Table 23: Characteristics Type G IT Leavers

Indicators for Type G Leavers. Type G leavers mentioned a broad variety of motivations for originally joining and reasons for leaving. Their relationships with others in the organization were average. While no single reason for leaving stands out, it seems that the combination of several different factors contributes to the decision to leave. If a certain threshold of negative aspects is reached, Type Gs suddenly decide to leave, making it difficult to identify specific reasons for their decision.

Retention Actions. Half of Type G leavers stated that their departure could have been prevented. As with the broad variety of joining motivations and leaving reasons, no clear, single action could have retained this type of IT employee. Thus, it is difficult to select one right retention action for Type Gs—financial compensation may be the only action that could retain a Type G IT employee.

> *"Honestly, the best retention strategy for [Type G IT employees] is money. They have various different reasons [for leaving]. ... Financial motivation works the best in such situations."* IT Manager

4.5 Addressing the Challenges of Retaining IT Professionals

Table 24 depicts how effective the five retention actions are for each of the seven types of IT employee. Each cell shows if the action is definitely helpful (a filled circle), might be helpful (a half-filled circle) or probably not helpful (an empty circle). We strongly recommend definitely helpful actions when trying to retain a particular type of IT employee. Might be helpful actions could be considered, but the probability of success is lower than for those actions identified as definitely helpful. Probably not helpful actions have a low probability of success. These actions can still be considered, but other retention actions should be applied first.

Retention Action/ Employee Type	Compensation	Working Arrangements	Career Development	Change of Department	Varying Work Tasks
A: “I have No Real Stock Here”	●	○	◒	◒	○
B: “This is the Wrong Job for Me”	○	○	●	○	●
C: “The Job Does Not Fit with my Spouse or Partner’s Needs”	○	◒	○	○	○
D: “I Do Not Like It Here“	○	○	◒	●	○
E: “I Need Something New“	○	○	●	◒	●
F: “I Lack Career Development Opportunities“	◒	○	●	●	○
G: “I Just Don’t Fit Here Anymore“	●	○	◒	○	○
● = Definitely helpful; ◒ = Might be helpful ; ○ = Probably not helpful					

Table 24: Retention Actions for Different Types of IT Employees

The table shows that it is unlikely that one overall retention action will be successful for all IT professionals because of their diverse reasons for joining the organization, their diverse ability to get along with others and their diverse attitudes to their job situation.

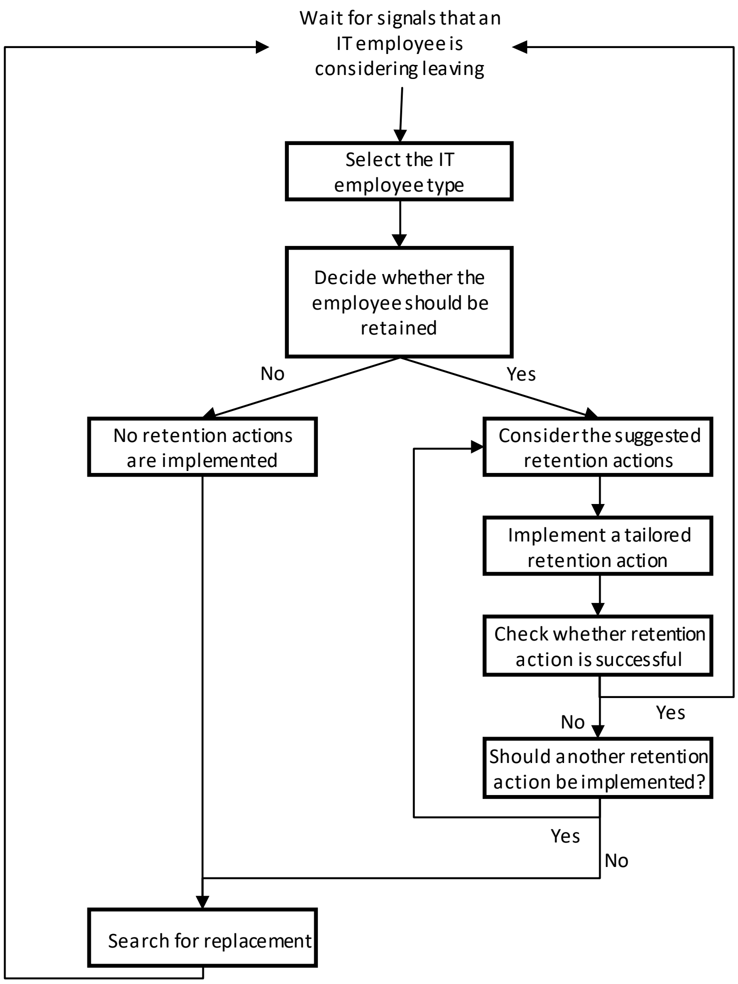

Figure 4: Choosing Retention Actions Is part of the Retention Process

4.6 Customizing the Retention Process Based on IT Employee Type and Proposed Retention Actions

Choosing the most effective retention actions for each type of IT employee is part of the larger retention process shown in Figure 4. The process starts when the IT manager senses weak signals that an employee is considering leaving. These signals can be related to private or professional life, and may include becoming a parent, updating a résumé on professional network sites like LinkedIn, or becoming less motivated at work. Some employees actively look for an opportunity to talk with their supervisor to express their dissatisfaction. According to the IT managers we interviewed, most of the time it is possible to predict quite well whether an employee is considering leaving.

After receiving weak signals that an IT employee is considering leaving, the manager assigns that individual to one of the seven types of IT employee. The decision on type is based on various indicators, such as observing the employee during daily work, feedback from co-workers, informal conversations or, for example, reaction to being asked to work overtime in critical project phases. Table 25 lists the personal characteristics that determine employee type.

Employee Type	Characteristics Identifying the Respective Employee Type
A: "I Have No Real Stock Here"	- Does not take ownership of problems - Seeks security in career perspectives - Not actively job seeking
B: "This Is the Wrong Job for Me"	- Requests changes in job responsibilities - Seeks challenging tasks - Fit in social environment
C: "The Job does Not Fit with my Spouse or Partner's Needs"	- Positive attitude to overtime as long as it fits private life - Strong personality - Changes in personal life
D: "I Do Not Like It Here"	- Many complaints about working environment - Poor relationship with supervisor - Actively thinks about leaving
E: "I Need Something New"	- Long time in same position - Positive attitude to current job - Seeks new tasks
F: "I Lack Career Development Opportunities"	- Missed promotion - Dissatisfied with working environment - Poor relationship with supervisor
G: "I Just Don't Fit Here Anymore"	- Various reasons for dissatisfaction - Does not respond to single retention actions

Table 25: Characteristics Identifying Employee Type

After identifying the individual's employee type, the IT manager needs to decide if that employee should be retained or let go. Usually, managers try to retain IT employees because of high demand in the job market, but there are exceptions—for example when the individual does not fit the organization.

It may not make sense to try and retain some types of IT employees—Type D ("I Do Not Like It Here"), for example, or Type F ("I Lack Career Development Opportunities"). These types of IT employees may have poor relationships with colleagues and supervisors and retaining them may have a harmful effect on the remainder of the team. Their dissatisfaction could hinder organizational processes and adversely affect the working climate within the whole department. On the other hand, Type B ("This Is the Wrong Job for Me") IT employees get along well with their co-workers and supervisor, but are unhappy with their assigned tasks. They might be worth keeping by assigning them to other tasks. The costs of any retention actions should also be taken into account when deciding whether to make the effort to retain an individual.

If the IT manager decides that the IT professional should not be retained, no retention actions are implemented and the search for a replacement begins.

Where the decision is to try and retain an IT employee, appropriate actions for the employee type, as shown in Table 24, are chosen and tailored to the specific situation. After implementing one of the retention actions, the IT manager assesses the effect of the action. If the outcome was not positive (i.e., the employee still plans to leave), then another retention action should be implemented. If all the retention actions do not stop the employee from leaving, the only recourse is to hire a replacement.

Experienced IT managers may already have their own actions for identifying employees considering leaving and for reducing IT employee turnover. However, our classification of IT employee types, the description of appropriate retention actions for each type and the retention process described above form the basis of a strategy for reducing the turnover rate of IT professionals that will be useful for less experienced managers. The elements of this strategy could, for example, be incorporated into managerial training programs.

> "*Our company has a special training program for IT managers. This retention framework could be a useful part of this training.*" IT Manager

4.7 Lessons Learned for Retaining IT Professionals

As well as developing the framework for a strategy for retaining IT professionals, our analysis of the survey of former employees of the German IT services provider and our interviews with IT managers at that firm revealed six lessons that will help managers to retain IT professionals.

4.7.1 Lesson 1: Know Your Employees

The relationship between IT manager and IT employee is very important. The manager will be better placed to identify those employees who might be considering leaving if he or she knows something about the employees, such as their motivations for originally joining the organization, their career goals and perhaps a bit about their private lives. Continually assessing the probability of an employee leaving may help the IT manager to intervene to prevent that happening.

To identify the most appropriate retention action for each employee type and tailor it to the specific situation, the manager has to know enough about the employee to assign her or him to an employee type. This requires more than the formal yearly performance review. Informal chats while having coffee or leaving the building together can provide opportunities for the manager to establish a trusting relationship with the employee or simply learn more about her or his professional and personal life. Informal chats, however, may be difficult to hold if the IT manager and the employee are not co-located. An IT manager we interviewed who manages a team of consultants working at a customer's site told us that he has established monthly audio conferences so he and the consultants can talk about things outside of daily business.

4.7.2 Lesson 2: Optimize Career Opportunities and the Internal Job Market

Our study shows that career development is an important retention action that is effective especially for IT employee Types B ("This is the Wrong Job for Me"), E ("I Need Something New") and F ("I Lack Career Development Opportunities"). Career development could also be appropriate for Types A ("I Have No Real Stock Here"), D ("I Do Not Like It Here") and G ("I Just Don't Fit Here Anymore"). IT employee Types B and E can be retained by assigning them to new and more challenging tasks. Developing a structured career plan specifically tailored to each individual IT employee that focusses on their individual strengths can also help to reduce turnover.

An internal job market, which allows IT employees to apply for a position within the organization without the permission of their supervisor, can provide opportunities both for career advancement and for working on new and diverse tasks. Experienced IT managers see internal job markets as an effective way of reducing turnover. Although the IT department might lose a valued staff member, it is probably better to lose an employee internally than to a competitor. Whether formal or informal, internal job markets should be designed to retain talent within the company.

4.7.3 Lesson 3: Align Retention Actions to the Organizational Context

IT managers have to consider the current context of the organization when they select retention actions. The size and structure of the organization determine whether certain retention actions are possible. For instance, Type E IT leavers ("I Need Something New") mentioned the desire to work abroad as a major reason for leaving. Larger organizations with offices around the globe can offer positions in another country; smaller nationally based businesses can't. Another factor to consider when selecting retention actions is the current workload. For instance, giving an employee a new task or assigning him or her to a new department may not be possible if the employee is key to the success of a project. Assuring the employee that he or she will be re-assigned to a new department as soon as the project is completed is an honest and open solution that demonstrates the manager's willingness to act in the interest of the employee. Providing training for the employee in preparation for the new task makes the manager's intentions more credible.

4.7.4 Lesson 4: Keep the Door Open

Some types of IT employee have good relationships within the organization and enjoy working for it. This is especially true for Types B ("This Is the Wrong Job for Me"), C ("The Job Does

Not Fit with my Spouse or Partner's Needs") and E ("I Need Something New"). These types generally leave because they dislike their assigned tasks or for personal reasons. IT managers should leave open the option of re-hiring these types of employee should their situation change in the future or should they change their mind. IT professionals who leave an organization for personal reasons have a positive attitude to the organization, and there is a high probability of them returning in the future. Maintaining personal contact and establishing alumni networks have been shown to be effective methods for re-employing former staff members.

4.7.5 Lesson 5: Conduct Post-entry Interviews

Post-entry interviews help to establish a personal rapport with a new employee and may help to identify at an early stage if he or she is at risk of leaving in the future. Conducting this type of interview at the six-month probation review may be too late to identify factors contributing to unhappiness. Early on, managers should understand the motivations of their employees for joining the organization and their career goals, so they can guide them in the right direction. Post-entry interviewees also give employees the feeling that the organization cares about them, their goals and their job satisfaction.

4.7.6 Lesson 6: Financial Compensation Leads to Short-term Retention

The retention actions described in this article have different short- and long-term effects. Whereas working arrangements, career development, department change and assignment to new tasks or projects lead to the retention of an IT employee in the mid- and longer-term, improved financial compensation generally only has a short-term effect because it does not adequately address the reason for employee dissatisfaction. While compensation is a form of appreciation, its impact dwindles over time.

IT managers should consider a combination of retention actions with different timescales for their effect. Financial compensation can be an action to buy time, which then allows for the implementation of another retention action with a longer-term effect. IT professionals, particularly younger ones, are more focused on career opportunities, interesting tasks and their private life than on financial compensation. Their job has to be diverse, appealing and fit their image of their life. IT managers have to consider a broader range of retention actions in the future to convince an employee to stay. Financial compensation by itself is an insufficient retention action.

Table 26 summarizes how each of these six lessons helps IT managers to overcome the challenges of retaining IT professionals.

Retainment Challenges	**Lessons Learned on How to Overcome Challenge**
Evaluate which retention strategies are effective	Know your employees
IT employees like to work on diverse tasks and desire career advancement	Optimize career opportunities; establish an internal job market
Retention actions have different requirements and consequences	Align the retention actions with the organizational context
Some employees that have left might consider re-joining the organization in the future	Keep the door open for re-employment
Get to know new employees early on and be attuned to recognizing early on those at risk of leaving in the future	Conduct post-entry interviews
Retention actions differ in their short- and long-term effects	Financial compensation leads to short-term retention, whereas working arrangements, career development, department change and assignment to new tasks or projects lead to retention in the mid- and longer-term

Table 26: Applying the Lessons Learned to Overcome IT Employee Retention Challenges

4.8 Concluding Comments

Turnover of IT professionals is problematic for IT organizations, and efforts should be taken to reduce or prevent it. IT managers should match retention actions with reasons for leaving, but because these reasons differ greatly according to the type of IT professional, it can be difficult to choose the most appropriate retention actions. We have proposed a strategy for retaining IT professionals, which classifies IT leavers (and employees) into seven types. We have provided advice on how so IT managers can choose the most effective retention actions for each of these types. We have also identified six lessons that IT managers can apply as they seek to reduce turnover among IT employees. Adopting our proposed strategy and implementing one or all of the lessons learned will provide a starting point for IT managers to reduce turnover rates among IT professionals.

4.9 Appendix: Research Method

We cooperated with a large German IT service provider, which wishes to remain anonymous. This vendor has a solid reputation in the industry and is among the 10 largest IT service providers in Germany. During the last decade, it has pursued a constant growth strategy. It generates most of its revenue through consulting projects, software development and large application hosting projects for clients from various industries including insurance, banking and automotive.

We followed a two-stage process for developing the classification of seven types of IT leavers and identifying retention strategies. First, the IT leaver types were derived from an analysis of the survey of 283 employees of the German services provider that had announced to leave. The survey questionnaire was distributed to the employees who had left between 2008 and 2013. To obtain a comprehensive depiction of the former employees, we asked about their original motivations for joining the firm, relationships within the organization retention actions that would have worked and the reasons for turnover were used for the formation of the cluster in order to obtain a comprehensive depiction of the employee. The data from this survey was processed by a clustering algorithm, which identified seven different clusters (i.e., types of IT leavers). These clusters were improved during subsequent interviews with IT managers at the service provider.

Second, we analyzed the triggers for leaving reported by survey respondents, and particularly any possible retention actions they mentioned. The focus of this analysis was on deriving retention strategies that could be applied by IT managers. These strategies were further developed and refined during subsequent interviews with eight IT managers at the services provider.

In addition to identifying the seven types of IT leavers and the corresponding retention actions, we developed a process for implementing the actions. This model was improved and revised during interviews with the IT managers.

5. The Explanatory Power of the Constructs of Transaction Cost Economics Theory

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Publication	International Research Workshop on Information Technology Project Management 2016
Status	Accepted
Contribution of First Author	Problem Definition, Research Design, Data Set Construction, Data Analysis, Interpretation, Reporting

Table 27. Fact Sheet Publication P7

Abstract

This Paper analyses the explanatory power of the constructs of transaction cost economics theory (environmental uncertainty, behavioral uncertainty, asset specificity and transaction frequency) in order to determine possible constructs for an endogenous theory of ITO. To analyze this, we employ a large project data set from a German IT outsourcing vendor. We find that only environmental uncertainty and transaction frequency have a high explanatory power and therefore should be considered for an endogenous theory of ITO. Behavioral uncertainty and asset specificity are only of minor relevance. The research is limited by the fact that we employed a data set from only one vendor. We contribute to theory by suggesting possible constructs for an endogenous theory of ITO and to practice by showing that the danger of opportunistic behavior is low. This paper contributes to the ongoing discussion on the applicability of transaction cost economics theory.

5.1 Introduction

The global information technology outsourcing (ITO) market has reached nearly $400bn in 2015 (Statista, 2016). ITO is defined as the assignment of an IT task to a vendor, who charges a fee for conducting the service (Apte et al., 1997; Lacity & Hirschheim, 1993; Loh & Venkatraman, 1992). These IT tasks can be various and range from “simple data entry to software development and maintenance, data center operations and full system integration” (Apte et al., 1997, p. 289).

Transaction Cost Economics is one of the leading frameworks for analyzing the phenomenon of ITO (Dibbern et al., 2004; Klein, 2002). It has also been frequently used for analyzing the chosen governance mechanism or for explaining the contract choice for ITO projects (e.g. Kalnins and Mayer (2004), Gefen et al. (2008) and Gopal et al. (2003)).

Recent studies about the role of TCE in ITO show inconsistent results (Karimi-Alaghehband et al., 2011; Lacity et al., 2011; Schermann et al., 2016). Schermann et al. (2016) conducted a meta-analysis about the influence of uncertainty, which is a central construct of TCE, on contract choice. Although TCE has been used for explaining the influence of various kinds of uncertainty, they found that the operationalization of uncertainty has a significant influence on the predictability of TCE. This supports the call by Karimi-Alaghehband et al. (2011) for a more rigorous application of TCE in ITO research. They conducted a literature review on the use of TCE in ITO studies and found that only a few studies use all constructs of the theory. However, Schermann et al. (2016) also found that the predictability of TCE significantly decreased after the year 1999. This supports the call by Lacity et al. (2011) to develop a new analytical framework for the ITO domain. In their literature review on the usage of TCE in ITO, they explain the found mixed results with the limited explanatory power of TCE.

However, there is limited empirical evidence that questions the application of TCO in ITO. Schermann et al. (2016) do not employ environmental and behavioral uncertainty, the two categories of uncertainty, mentioned by Williamson (1985). They rather focus on the construct task uncertainty. Analyzing the explanatory power of the original constructs instead of derived ones gives a better picture whether the original theory is applicable. Furthermore, other TCE constructs beyond uncertainty, such as asset specificity and transaction frequency have not been examined.

Other issues are related to meta-analyses. First, they are based on subjective coding of heterogeneous samples, differing in project and company size, time frame, and variable operationalization. Second, meta-analyses and literature analyses are subject to the file drawer problem, which might be especially an issue when examining the explanatory power of a theory (Borenstein, Hedges, Higgins, & Rothstein, 2009). It argues that studies with significant results tend to get published more often. Therefore, meta-analyses and literature analyses rely on a biased data basis.

Lacity et al. (2011) call for the development of a new analytical framework. However, it remains unclear which constructs should be part of this framework. TCE consists of different individual constructs that could be part of a newly developed framework. However, the relevance of the individual constructs remains unclear. In order to address this research gap, we formulate the following research question to address the previously discussed situation: *How well do the individual TCE constructs explain the governance choice in ITO transactions?*

To address this research question, we conducted an empirical study with a unique quantitative data set from a German ITO vendor, called ALPHA. The data set covers all projects conducted by ALPHA between 1995 and April 2014. The initial data set contains more than 36,000 projects for about 2,000 different clients.

We find that environmental uncertainty is the only important TCE construct that has a huge explanatory power. We conclude that a new analytical framework should contain environmental uncertainty as a central construct.

The remaining sections of this paper are structured as follows. First, we present the theoretical background of the paper and develop our hypotheses. Then, we explain our research method including the employed variables. After that the results of the data analysis are shown. Finally, the paper ends with a discussion of the found results.

5.2 Theoretical Background

The three central constructs of TCE are uncertainty, transaction frequency and asset specificity (Williamson, 1985). Uncertainty can be further divided into environmental and behavioral uncertainty (Williamson, 1985). Environmental uncertainty is related to uncertainty that stems from the lack of knowledge about the future state regarding the environment of the transaction (Susarla et al., 2009). Behavioral uncertainty deals with uncertainty that originates from the lack of knowledge regarding the actions of the in the transaction involved actors (Susarla et al., 2009).

Asset specificity is defined as the "degree to which the assets used to conduct an activity can be redeployed to alternative uses and by alternative users without sacrifice of productive value" (Williamson, 1996). It can be divided into site specificity (geographical site of investment), physical asset specificity (Equipment and tools) and human asset specificity (knowledge and learning of employees) (Karimi-Alaghehband et al., 2011).

Transaction frequency focuses on the recurrence of activities that are needed for the transaction (Karimi-Alaghehband et al., 2011). Transactions can occur only occasionally, but also permanently.

The extent to which TCE has been employed varies. According to Carter and Hodgson (2006), only a few studies analyze all three constructs. This is as well criticized by Lacity and Khan (2016). According to Karimi-Alaghehband et al. (2011), although transaction frequency and asset specificity might be non-significant, they should be included in studies.

TCE is used for explaining two decisions made by the customer: whether to outsource or not, which is known as the make-or-by decision, and for choosing the mode of governance (Williamson, 1991). In this paper, we focus on the second decision, namely on the chosen governance mechanism, which is predominantly determined by the type of contract.

The two prevalent types of ITO contracts are fix-price (FP) and time and material (TM) contracts (Gopal et al., 2003; Lichtenstein, 2004). In FP contracts, the ITO vendor agrees to deliver a predefined result and is compensated with a certain fee (Ethiraj et al., 2005). TM contracts are different because the billing is based on the agreed hourly rate and the working hours that the ITO vendor invested (Ethiraj et al., 2005).

The behavioral uncertainty component of TCE has been used to explain how the familiarity between the vendor and the client influences the contract choice. Increased familiarity decreases the danger of opportunistic behavior and therefore leads to increased TM contracting (Gefen et al., 2008; Kalnins & Mayer, 2004).

Factors, such as project duration, project volume or requirements uncertainty of the project can also be assigned to the uncertainty component of TCE (Lacity & Khan, 2016; Schermann et al., 2016). To be more precise, they are part of the environmental uncertainty. It has been found that higher project related uncertainty increases TM contracting (Gefen et al., 2008; Gopal et al., 2003; Kalnins & Mayer, 2004; Susarla et al., 2009).

Asset specificity has been rarely used to explain the contract choice. Susarla et al. (2009) analyzed the influence of client specific investments by the vendor, but did not find a significant influence.

Recently, there have been studies that have found empirical inconsistencies between the prediction based on TCE and the observed results (Karimi-Alaghehband et al., 2011; Lacity et al., 2011). Karimi-Alaghehband et al. (2011) call for a more rigorous operationalization of TCE constructs and the usage of all constructs of the theory. Schermann et al. (2016) have shown that the magnitude of the relationship between uncertainty and the choice of governance mechanism is dependent on the operationalization of uncertainty. However, they have not used all TCE constructs, which has been criticized by Lacity and Khan (2016).

Opposed to the call of Karimi-Alaghehband et al. (2011) for a more rigorous operationalization of TCE constructs, Lacity et al. (2011) call for the development of an endogenous theory of ITO. They argue that the research on ITO has already matured to the point that an own theory makes sense. However, Lacity et al. (2011) only give broad propositions that could be part of the newly developed theory, but they argue for further research. They argue that a data driven theory development approach should be taken, as a theory based on data is more difficult to refute (Glaser & Strauss, 2009).

As some of the TCE constructs have received empirical support (Karimi-Alaghehband et al., 2011; Lacity et al., 2011), we focus on the evaluation which of the TCE constructs could be part of a newly developed endogenous theory of ITO. Therefore, we analyze the explanatory power of environmental uncertainty, behavioral uncertainty, asset specificity, and transaction frequency for choosing the governance mechanism.

IT projects are characterized by a high degree of uncertainty, such as the certainty of the requirements or changing technology (Nidumolu, 1995; Schwartz & Zozaya-Gorostiza, 2003). In general, the environmental uncertainty of transactions is very high in the ITO domain. The governance mechanism determines the flexibility of the transaction. For instance, it is quite easy to change requirements in a TM contract, but it is hardly possible under a FP contract (Gefen et al., 2008; Gopal et al., 2003). Environmental uncertainty has a high relevance in the ITO domain. Therefore, we formulate the following hypothesis:

H1: Environmental uncertainty has a high level of explanatory power

According to Williamson (1985), behavioral uncertainty is paramount to environmental uncertainty. It has been used by several ITO studies (e.g. Kalnins and Mayer (2004), Gopal et al. (2003) or Gefen et al. (2008)) for explaining the development of the ratio of TM and FP contracts over the customer lifetime. However, we argue that behavioral uncertainty is not of high relevance in the ITO domain. The ITO market is characterized with a high degree of competition (Manning et al., 2011). Acting opportunistically always has the danger that it comes out. This would destroy the reputation of the vendor and might even be fatal (Dibbern, Winkler, & Heinzl, 2008; Dongus et al., 2014). ITO vendor extensively focus on building up a good reputation in their relationship with their customer, as this is a source for future business (Goles, 2001; Levina & Ross, 2003). Therefore, it is quite unrealistic that there is a high danger of opportunistic behavior by the vendor. Because of this, the following second hypothesis is formulated:

H2: Behavioral uncertainty has a low level of explanatory power

According to Riordan and Williamson (1985), asset specificity has the greatest impact of all four TCE constructs. However, it remains unclear, whether this is also the case in the ITO domain. We argue that asset specificity has a low explanatory power in the ITO domain. Most of the asset specificity of an ITO vendor is related to human asset specificity. As IT employees are quite mobile and can easily work for other customers, the asset specificity in the ITO domain is not important. Furthermore, due to the high demand of ITO during the last years, it is easily possible to find a second best use for an IT employee. Therefore, we formulate the following third hypothesis:

H3: Asset specificity has a low level of explanatory power.

Transaction frequency has not received any empirical support (Karimi-Alaghehband et al., 2011; Lacity et al., 2011). A high frequency brings economies of scale regarding governance costs (Miranda & Kim, 2006). For instance, FP contracts are more expensive to set up than TM contracts. These costs can be distributed over several contracts, if the transaction frequency is high. Due to the missing empirical support, we expect a low explanatory power of transaction frequency. Therefore, we formulate the following first hypothesis:

H4: Transaction frequency has a low level of explanatory power.

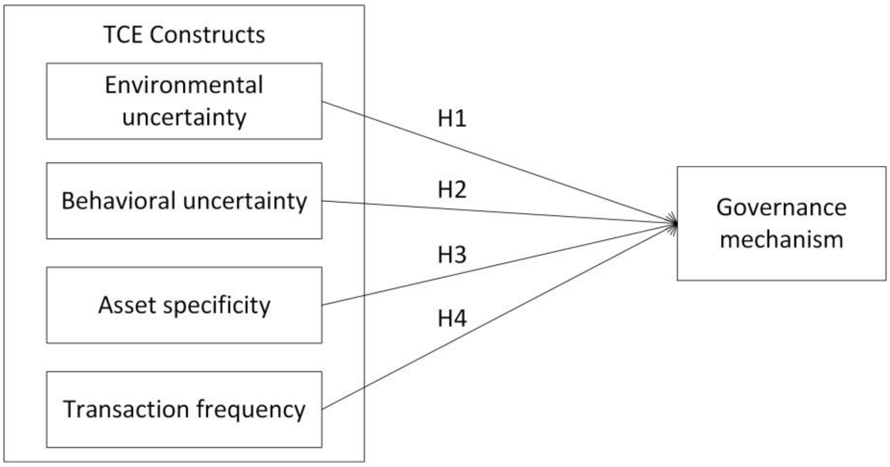

Figure 5: Research Model

5.3 Research Method

To address these hypotheses, we collected quantitative data from ALPHA, a large German IT service provider. ALPHA generates most of its revenue through consulting projects, software development and hosting for clients from various industries, such as insurance, banking and automotive. It has offices in more than 20 countries, but the majority of the business is conducted in Germany, Switzerland, Austria and the US. ALPHA has been founded in the early 1980s and therefore can be seen as a successful and established company.

The data have been extracted directly from the project controlling system of ALPHA who granted us access to all 36,413 projects conducted between January 1995 and April 2014. The information on the projects is of high quality because it was extracted from the project controlling system of ALPHA, which is also used for billing clients. Additionally, directly accessing quantitative data is not subject to recall bias, which could be a problem in case studies and surveys (Gefen et al., 2008).

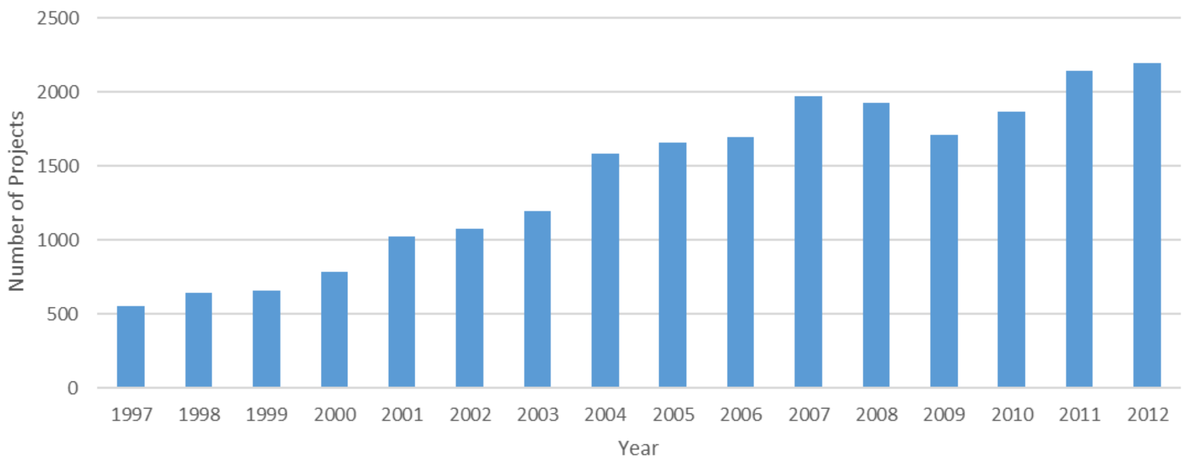

Figure 6: Distribution of Projects over the years

We removed the years before 1997, in order to calibrate the data set. The first project of a customer should really be the first one and not simply the start of the data set. The number of short projects increases towards the end of the data set as it includes only finished projects. To address this issue, the projects from 2013 and 2014 were removed to have a realistic composition of projects. Additionally, we filtered out internal projects and removed projects with incomplete data. The final data set contains 22,701 projects for 1,736 different customers. Figure 6 shows the distribution of these projects over the years 1997 to 2012.

5.3.1 Variables

The dependent variable is the chosen *governance mechanism* of the transaction. This is mostly determined by the contract type of the project. The contract type has also been used by other TCE studies as a proxy for the chosen governance mechanism (Schermann et al., 2016). We focused on the two prevalent types of ITO contracts, namely FP and TM contracts (Gopal et al., 2003; Lichtenstein, 2004). We coded FP as 1 and TM as 0. The type of ITO contract determines which party has to bear additional costs in case a realignment of the transaction is necessary (Hoermann et al., 2015).

The independent variables are environmental uncertainty, behavioral uncertainty, asset specificity and transaction frequency, that are described in the following paragraphs.

Environmental uncertainty: We used the volume of the project as a proxy for the uncertainty of the project which largely determines environmental uncertainty (Tiwana & Bush, 2007). Larger projects tend to have a higher uncertainty and to be more complex (Banerjee & Duflo, 2000; Gopal et al., 2003). As TM contracts allow more flexibility, the costs for realigning the transactions are lower. We employed the total hours worked for the project for approximating the project volume.

Behavioral uncertainty: The danger of opportunistic behavior is closely linked to the business familiarity between the customer and the vendor (Gefen et al., 2008). We employed the volume of prior contracts with the same customer as a proxy for customer familiarity. Another possibility is to measure it with the number of prior contracts (Gefen et al., 2008; Gopal et al., 2003). We have chosen the volume of prior contracts, because according to Gefen et al. (2008) it is better measured as the volume of prior contracts.

Asset specificity: We employed the average customer knowledge within the team, approximated by the average hours previously worked for the customer, as a proxy for asset specificity. Project team members gain knowledge about the customer during the conductance of a project. This knowledge is a form of asset that is most of the time can only be leveraged and is specific for a single customer. We only considered human assets, as site specificity and physical specific assets only play a minor in ITO (Aubert & Rivard, 2016).

Transaction frequency: The number of projects in a timeframe of 180 days prior and after the project start with the same customer has been employed as a proxy for transaction frequency. Transaction frequency describes the activity of the customer in the market. As multi-vendor sourcing has gotten the dominant type of ITO in recent years (Dibbern et al., 2004), it can be assumed that a high number of transactions between ALPHA and a customer is a sign that this customer is an highly active customer in the market. Also future projects have been considered, because there is often a gap of several months between the first contacts between the vendor and the client, the signing of the contract and the actual project start. Furthermore, a vendor often can estimate the number of projects that will be conducted with the same customer in the following months quite well.

5.3.2 Data Analysis

As the dependent variable is dichotomous, we employed logistic regression. To analyze the explanatory power of the different TCE constructs several different regression models have been constructed, where each time a specific construct has been excluded. We use Nagelkerke's R2 for analyzing the explanatory power of the different constructed models (Nagelkerke, 1991). We assume that a decrease in Nagelkerke's R2 by more than 10% is a sign of high explanatory power.

The following table shows some descriptive statistics of the employed subsets. Due to high skewness of project volume, customer familiarity, customer knowledge within team and transaction frequency, these variables are log-transformed (Hair et al., 2006).

Variable	Unit	Min	Mean	Median	Max	SD
Contract Type	0 = TM 1 = FP	0	0.4155324	0	1	0.4928244
Project Volume	Hours worked	0.25	1002.982	225.5	659172.5	6368.622
Customer familiarity	€ previous revenue	0	53,012,900	13,823,879	292,559,516	76,722,173
Customer Knowledge within Team	Hours	0	4,007.877	2,179.758	60,978.35	5,567.415
Transaction Frequency	#	1	38.29237	12	227	46.65994

Table 28. Descriptive Statistics (n=22,701)

The following tables show the correlation matrix of the employed variables.

	1)	2)	3)	4)	5)
1) Contract type	1.000				
2) log(Project Volume)	-0.130 ***	1.000			
3) log(Customer familiarity)	0.190 ***	0.168 ***	1.000		
4) log(Customer Knowledge within Team)	0.229 ***	0.145 ***	0.655 ***	1.000	
5) log(Transaction Frequency)	0.319 ***	0.022 ***	0.730 ***	0.649 ***	1.000

Table 29. Correlation Matrix (n=22,701)

5.4 Results

Dependent variable: Contract type (0 = TM; 1 = FP)					
Variable	**Model 1 – Base model**	**Model 2 – H1 without environmental uncertainty**	**Model 3 – H2 without behavioral uncertainty**	**Model 4 – H3 without asset specificity**	**Model 5 – H4 without transaction frequency**
Intercept	-0.171653 ** (0.061289)	-0.906944 *** (0.049833)	-0.469704 *** (0.050874)	-0.211724 *** (0.061165)	-0.624506 *** (0.063302)
log(Project volume)	-0.181932 *** (0.008724)		-0.194560 *** (0.008604)	-0.173582 *** (0.008665)	-0.222016 *** (0.008478)
log(Customer familiarity)	-0.041345 *** (0.004957)	-0.059211 *** (0.004784)		-0.023297 *** (0.004640)	0.049687 *** (0.004324)
log(Customer Knowledge within Team)	0.063589 *** (0.005842)	0.052702 *** (0.005757)	0.047621 *** (0.005426)		0.115304 *** (0.005434)
log(Transaction Frequency)	0.399719 *** (0.013206)	0.439606 *** (0.012933)	0.337646 *** (0.010747)	0.444348 *** (0.012623)	
Nagelkerke’s R2	0.1671814	0.1435973	0.163638	0.1608902	0.1160723
%-change of R2		14,1%	2,1%	3,8%	30,6%
Significance: *** = significant at the 0,1% level; **= significant at the 1% level; *= significant at the 5% level, †=significant at the 10% level					

Table 30. Results for constructed logistic regression models

The base model has a Nagelkerke’s R2 of 16,7%. We find that all variables of the base model are highly significant.

For testing the first hypothesis, the project volume, which is a proxy for environmental uncertainty, has been excluded from the base model. We find that Nagelkerke’s R2 drops by 14.1% to 14.4%. This is the second largest decrease and significantly higher than the third and fourth largest decrease. Therefore, hypothesis H1 is supported.

If customer familiarity, which is used as a proxy for behavioral uncertainty, is excluded, R2 only decreases by 2.1%, which is the smallest decrease of all constructs. As hypothesis H2 claims that behavioral uncertainty only has a low explanatory power, H2 is supported.

For testing hypothesis H3, we excluded asset specificity from the base model. We find that Nagelkerke’s R2 only slightly drops by 3.8% from 16.7% to 16.1%. As this is the second smallest decrease and by far smaller than third smallest one, we can conclude that H3 is supported.

If transaction frequency is excluded from the base model, Nagelkerke’s R2 decreases by 30.6% to 11.6%. This is the largest drop of all, but hypothesis H4 claimed that transaction frequency only has a low explanatory power, it is rejected.

5.5 Discussion

Our results show that most of the explanatory power of TCE is based on only two constructs, namely environmental uncertainty and transaction frequency. The other two TCE constructs, behavioral uncertainty and asset specificity, do not seem to be that important. Therefore, environmental uncertainty and transaction frequency should be considered as possible new constructs for a new endogenous theory of ITO that should be developed after Lacity et al. (2011).

Before discussing the contribution of our results, limitations of our approach and data analysis are presented. First, the employed data set comes from only one vendor, which is a threat to the generalizability of the results. On the other hand, data from the same vendor and multiple clients cancels out vendor specific effects and makes it possible to more thoroughly focus on the individual TCE constructs. Second, the chosen proxies for the TCE constructs might not be the perfect proxies. However, we employed proxies that have also been used by previous studies and have proven to be reliable. Furthermore, as we are dealing with data from an ITO service provider, we are limited to the available variables and cannot define our own variables.

We contribute to theory by showing that most of the explanatory power of TCE within the ITO domain is due to environmental uncertainty and transaction frequency. Therefore, these two constructs are candidates to be included in the newly developed endogenous theory of ITO after Lacity et al. (2011).

The high relevance of environmental uncertainty is opposed to Williamson (1985) who argues that behavioral uncertainty should be paramount to environmental uncertainty. Environmental uncertainty is the dominant type of uncertainty in the ITO domain. This could be mainly due to the fact that IT projects have in general a high degree of uncertainty (Nidumolu, 1995; Schwartz & Zozaya-Gorostiza, 2003). The higher the uncertainty of an ITO transaction, the higher the flexibility of the governance mechanism should be.

Furthermore, this is the first study that shows that transaction frequency has a high influence on the chosen governance mechanism. According to the literature reviews of Karimi-Alaghehband et al. (2011) and Lacity et al. (2011) no other study has found a significant influence of this TCE construct.

Our results suggest that behavioral uncertainty and asset specificity should not be part of a newly developed endogenous theory. The ITO market is characterized with a high degree of competition (Manning et al., 2011). Acting opportunistically always has the danger that it comes out. This would destroy the reputation of the vendor and might even be fatal (Dibbern et al., 2008; Dongus et al., 2014). Therefore, it is quite unrealistic that there is a high danger of opportunistic behavior by the vendor.

The conducted analyses suggest that asset specificity has hardly any influence in the ITO domain. This is opposed to Riordan and Williamson (1985) who argue that it has the hugest influence of all TCE constructs. From the perspective of an ITO vendor, most of the asset specificity is related to human asset specificity. Human assets are quite mobile and can be used easily work for other customers. This is different in manufacturing where a vendor might have invested in specific tools for being able to fulfill the requirements of the customer. Another explanation could be that due to the high demand of ITO during the last years, it is easily possible to find a second best use for an IT asset.

We contribute to practice by examining factors that determine the contract choice. We find that behavioral uncertainty and the danger of opportunistic behavior does not explain the choice of governance mechanism, which is opposed to findings by Gefen et al. (2008) and Gopal et al. (2003). Therefore, clients do not have to focus on trust issues in the ITO domain. Furthermore, we show the influence of client specific characteristics that should be considered while choosing the appropriate type of contract.

This is only a first step towards an endogenous theory of ITO. Other possible constructs and their influence on the choice of governance mechanism should be analyzed.

6. Are We Already in a Mature ITO Market? A Longitudinal Study on the Effects of Market Maturity on ITO Vendor Project Performance

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Status	Accepted
Contribution of First Author	Problem Definition, Research Design, Data Set Construction, Data Analysis, Interpretation, Reporting

Table 31: Fact Sheet Publication P9

Abstract

Studies on information technology outsourcing (ITO) have shown different results for the influence of prior interaction and contract type on the project performance of the ITO vendor. The ITO market maturity could provide an explanation for these differences. However, it is not clear how to separate the ITO market into different maturity phases to gain insight into any possible effect maturity might have on project performance. We used a large data set from an ITO vendor to analyze this research gap. We find that the ITO market has increased its maturity and can be separated into an immature phase, occurring between 1997 and 2001, a transition phase, occurring between 2002 and 2008 and a third phase which occurred after 2008. This identification of different phases of ITO market maturity will contribute to a deeper understanding of the influence of ITO market maturity on the project performance of ITO vendors.

6.1 Introduction

According to a study of Gartner (2013), the global information technology outsourcing (ITO) market will reach $288bn in 2013 with steady growth during the next several years. ITO is defined as the assignment of an IT task to a vendor, who charges a fee for conducting the service (Apte et al., 1997; Lacity & Hirschheim, 1993; Loh & Venkatraman, 1992). These IT tasks can vary ranging from “simple data entry to software development and maintenance, data center operations and full system integration” (Apte et al., 1997, p. 289). ITO services have become commoditized during the last years (Manning et al., 2011), which increased the competition between ITO vendors. Additionally, clients have gained more experience with the selection of the right vendor having learned from mistakes made in previous relationships (Lacity et al., 2010; Manning et al., 2011). Several studies argue that the ITO market has increased its maturity during the last two decades (Bapna, Gupta, Ray, & Singh, 2013; Dongus et al., 2014; Stadtmann & Kreutter, 2009; Suarez et al., 2013; Susarla & Barua, 2011). In order to survive in such a market, ITO vendors need to know how factors, such as client knowledge or contract type, contribute to the performance of their projects.

Empirical studies on the influence of client knowledge, which can be approximated through prior interaction, on the project performance of the ITO vendor have shown contradicting results. While most of the studies show prior interaction has a negative influence (Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014), Ethiraj et al. (2005) found a positive relationship. As the data set employed in these studies cover different maturity phases, we analyze the moderating role of ITO market maturity on the relationship between client knowledge and project performance of the ITO vendor.

Previous studies have found that fix-price contracts have a negative influence on project performance of the ITO vendor (Ethiraj et al., 2005; Gopal et al., 2003), but the data sets in these studies comprised projects conducted prior to 2001, defined as the on-set of ITO market maturity by Susarla and Barua (2011) and Dongus et al. (2014). Dongus et al. (2014) found that the contract choice differs between the immature and mature phase of the ITO market. Therefore, we focus on the moderating role of market maturity on the relationship between contract type and project performance.

We formulated the following research question to address these identified gaps in our knowledge of the influence of ITO market maturity: How d*oes the influence of client knowledge and contract type on project performance of the ITO vendor differ based on the maturity of the ITO market?*

To address our research question it is necessary to divide the ITO market into different phases based on the level of maturity. Susarla and Barua (2011) and Dongus et al. (2014) argue that the ITO market reached maturity after 2001. Other authors have identified 1998 (Suarez et al., 2013) and 2006 (Stadtmann & Kreutter, 2009) as the years maturity was reached. Bapna et al. (2013) did not explicitly identify a date, but treated the maturation as a continuous process. These different concepts call for further research.

We conducted an empirical study with a unique quantitative data set from a German ITO vendor, called ALPHA. The data set covers all projects conducted by ALPHA between 1995 and April 2014. The extended time period makes it possible to analyze the maturation of the ITO market. The initial data set contains more than 36,000 projects for about 2,000 different clients. We find that the ITO market has increased its maturity and can be divided into an immature phase, which occurred between 1997 and 2001, a transition phase, between 2002 and 2008, and a third phase which occurred after 2008. Whether this latter phase is a mature or a second transition phase will be addressed in future research.

The remaining sections of this paper are structured as follows. First, we present background information on project performance and ITO market maturity. This is followed by an explanation of our research model and the hypotheses that are examined are developed. We then present the research method and the studies' preliminary results. The paper ends with our plans for future research on the topic.

6.2 Background on ITO Vendor Project Performance and Market Maturity

6.2.1 Project Performance

Lacity et al. (2010) reviewed literature on empirical ITO studies. According to their results, only 8 of 741 analyses considered the ITO vendor's business performance as the dependent variable. To approximate business performance, several measures, such as the project profitability (Gopal & Koka, 2010; Hoermann et al., 2015; Schermann et al., 2014), the absolute profits (Ethiraj et al., 2005; Gopal & Koka, 2012; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003) and the project price (Gefen et al., 2008) have been employed. Project performance is a complex construct influenced by many factors including client knowledge and contract type.

Repeat interactions increase the ITO vendor knowledge of the processes, structures and technologies of the client (Banerjee & Duflo, 2000; Chen & Bharadwaj, 2009; Mani et al., 2013). Therefore, the vendor better understands the needs of the client and the tasks of relevance for the project (Chen & Bharadwaj, 2009). This knowledge should increase project performance, an argument supported by the findings of Ethiraj et al. (2005). Other studies indicate that prior interaction has a negative effect on the project performance of the ITO vendor (Gopal et al., 2003; Hoermann et al., 2015; Schermann et al., 2014). Gopal et al. (2003) argue that their result could be specific to the market analyzed in their study. Another explanation for the negative effect is the increasing complexity occurring in future projects with the same client (Hoermann et al., 2015) or that the vendor from time to time engages in explorative organizational learning activities which have a negative impact on profitability (March, 1991; Schermann et al., 2014).

The two prevalent types of ITO contracts are fix-price (FP) and time and material (TM) (Gopal et al., 2003; Lichtenstein, 2004). In FP contracts, the ITO vendor agrees to deliver a predefined result and is compensated with a certain fee (Ethiraj et al., 2005). TM contracts are different because the billing is based on the agreed hourly rate and the working hours invested by the ITO vendor (Ethiraj et al., 2005). Previous studies have found that FP contracts have a negative influence on project performance of the ITO vendor (Ethiraj et al., 2005; Gopal et al., 2003).

Gefen et al. (2008) did not find a significant influence of the type of contract on project performance.

6.2.2 ITO Market Maturity

Several studies argue that the ITO market is in a mature phase (Dongus et al., 2014; Stadtmann & Kreutter, 2009; Suarez et al., 2013; Susarla & Barua, 2011). In general, the theory on industry life-cycle assumes that at a certain point in time a structural change occurs transforming the industry from a growth (immature) phase to a mature phase (Agarwal et al., 2002; Williamson, 1975). The immature phase is characterized by high uncertainty, rapid market growth, an increasing number of firms and a low market concentration. The mature phase is associated with low uncertainty, decrease of market growth to a normal rate, domination of the market by a stable number of companies and a high market concentration (Agarwal et al., 2002; Klepper, 1996; Klepper & Graddy, 1990; Mazzucato & Semmler, 1999; Thorelli & Burnett, 1981; Williamson, 1975). The industry life-cycle can be separated into different phases (Agarwal et al., 2002; Avnimelech & Teubal, 2006; Cusamano et al., 2015; Klepper, 1996; Klepper & Graddy, 1990; Williamson, 1975). Cusamano et al. (2015) focus on the lifecycle of service industries and argue that three phases exist: ferment, transition and mature. A similar three-phase model has been proposed by Klepper and Graddy (1990).

According to Susarla and Barua (2011) and Dongus et al. (2014), the ITO market entered into a mature phase after the year 2001. They argue that the collapse of the internet sector acted as an endogenous shock to change the market. However, Suarez et al. (2013) argue that the mature phase began in 1998. Employing a certain point of time for separating the maturity phases assumes that the market matured in a very short timeframe. Bapna et al. (2013) used a continuous time dependent variable for measuring ITO market maturity, which suggests that maturation is an ongoing activity. A transition phase, as proposed by Klepper and Graddy (1990), has only been assumed by Stadtmann and Kreutter (2009) who argue that the ITO market was in a transition phase between 2000 and 2006.

6.3 Research Model and Hypotheses

The previously described different concepts for separating the ITO market call for further research. Based on the market maturity model proposed by Klepper and Graddy (1990) and Cusamano et al. (2015), the following hypothesis is proposed:

H1: The ITO market can be separated into immature, transition and mature phases.

One possibility to measure ITO market maturity is the probability of opportunistic behavior by the vendor. The literature on transaction cost economics argues that the danger of opportunistic behavior is a central construct of exchange relationships (Williamson, 1979). According to Williamson (1985) and Hill (1990) the probability of opportunistic behavior increases with uncertainty. Uncertainty makes it difficult to distinguish opportunistic from cooperative vendors (Hill, 1990). As previously mentioned, uncertainty in the market differs between the different phases of market maturity (Agarwal et al., 2002; Klepper, 1996; Klepper & Graddy, 1990). Therefore, the probability of opportunistic behavior is dependent on the market maturity. This view is supported by Argyres and Bigelow (2007) who found that the effect of transaction cost economics is dependent on industry maturity and Dongus et al. (2014) who found that transaction cost economics is only relevant in the immature phase of the ITO market.

Clients try to protect themselves from opportunistic behavior through their choice of contract (Kalnins & Mayer, 2004; Susarla & Barua, 2011). FP contracts decrease the possibility of the vendor to act opportunistically because the delivery of a predefined result has been agreed upon and any cost overruns are borne by the vendor (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Lichtenstein, 2004).

Asymmetric knowledge between the vendor and the client, which tends to occur during their initial interactions, also enables opportunistic behavior (Williamson, 1985). Furthermore, if only a few interactions have occurred, the client does not know whether the vendor tends to act opportunistically (Gefen et al., 2008; Hill, 1990). Therefore, the choice of contract for the first few interactions can be used as a proxy for market maturity.

H1a: The ITO market can be separated into immature, transition and mature phases based on the contract choice for the first few interactions between the ITO vendor and the client.

A second possibility for measuring maturity is the market concentration of the ITO market. The number of participants decreases to a stable number in the mature market (Agarwal et al., 2002; Klepper, 1996). As the market size does not decrease accordingly, the market concentration can be used as an indicator for market maturity (Agarwal et al., 2002; Mazzucato & Semmler, 1999; Thorelli & Burnett, 1981). Therefore we formulate the following hypothesis:

H1b: The ITO market can be separated into immature, transition and mature phases based on the concentration of the ITO market.

The influence of ITO market maturity on the relationship between client knowledge and project performance has not yet been examined. Suarez et al. (2013) analyzed the direct influence of maturity on the operation margin of software vendors, but they did not find a significant influence. Karniouchina, Carson, Short, and Ketchen (2013) argue that the determinants of firm performance are different between the stages of the industry life-cycle. As previously mentioned, results on the relationship between client knowledge of the vendor and project performance are contradictory. The data set of Hoermann et al. (2015) and Schermann et al. (2014) covers the time between 2004 and 2011 and therefore comes from the mature ITO market according to the definition provided by Susarla and Barua (2011), Dongus et al. (2014) and Suarez et al. (2013). Ethiraj et al. (2005) and Gopal et al. (2003) employed data sets with projects conducted prior to 2001. Their data sets, therefore, might differ in respect to the maturity of the ITO market.

Through repeated interaction with the same client, the vendor gets to know the client’s capabilities, its business environment and its culture (Kalnins & Mayer, 2004). During repeated interactions with the same client, the vendor tries to develop knowledge about the client which might lead to a competitive advantage and enable the vendor to increase project profitability. However, this is dependent on the maturity of the ITO market.

First, the bargaining power of the vendor decreases with increased maturity. According to Manning et al. (2011), ITO services have become commoditized in recent years. Bapna et al. (2013) found that multi-sourcing increases with ITO market maturity. These developments increase the competition between the ITO vendors and decrease the client's dependence on the vendor which makes switching the ITO vendor easier (Gopal et al., 2003; Manning et al., 2011). Additionally, clients have become more familiar with ITO during the last several years (Lacity et al., 2010).

Second, ITO vendors might be forced to continuously develop new capabilities in a mature market. Schermann et al. (2014) argue that the vendor engages in explorative organizational learning activities with the client from time to time. These projects are associated with higher risk and a lower expected project profitability (March, 1991). Because the competition on the ITO market has increased (Manning et al., 2011), ITO vendors might engage in more explorative projects to differentiate themselves from competitors.

Because of changes in vendor bargaining power and the continuous need for vendors to develop new capabilities in a mature market, it is difficult for ITO vendors to leverage client knowledge and demand higher prices. Therefore the following hypothesis has been formulated:

H2a: Client knowledge can be leveraged and therefore increases the project performance of the ITO vendor in the immature ITO market but not in the mature ITO market.

According to findings by Gopal et al. (2003) and Ethiraj et al. (2005), FP contracts, in comparison to TM contracts, have a negative influence on the project performance of the ITO vendor. The data sets used in those studies, however, comprise projects conducted prior to 2001. These results are contradicting: the vendor should be compensated for taking higher risks in FP contracts as it bears all possibly occurring cost overruns (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Lichtenstein, 2004). Perhaps the relationship found by Gopal et al. (2003) and Ethiraj et al. (2005) was due to the immature ITO market where FP contracts are used as a protection against opportunistic behavior for the first few projects (Dongus et al., 2014; Williamson, 1985).

FP contracts have a negative influence during the immature phase of the ITO market. The prevalent high uncertainty makes it difficult to estimate the project and therefore leads to contractual gaps which need to be closed during the project (Williamson, 1979). These renegotiations create additional costs and lead to lower profitability (Hoermann et al., 2015; Williamson, 1979). On the other hand, FP contracts have a positive influence in the mature market because uncertainty is lower. Furthermore, ITO vendors have improved their competences in recent years (Lacity et al., 2009) and should, therefore, be more capable of efficiently managing FP projects.

H2b: FP contracts in comparison to TM contracts have a negative influence on project performance of the ITO vendor in the immature market and a positive influence in the mature ITO market.

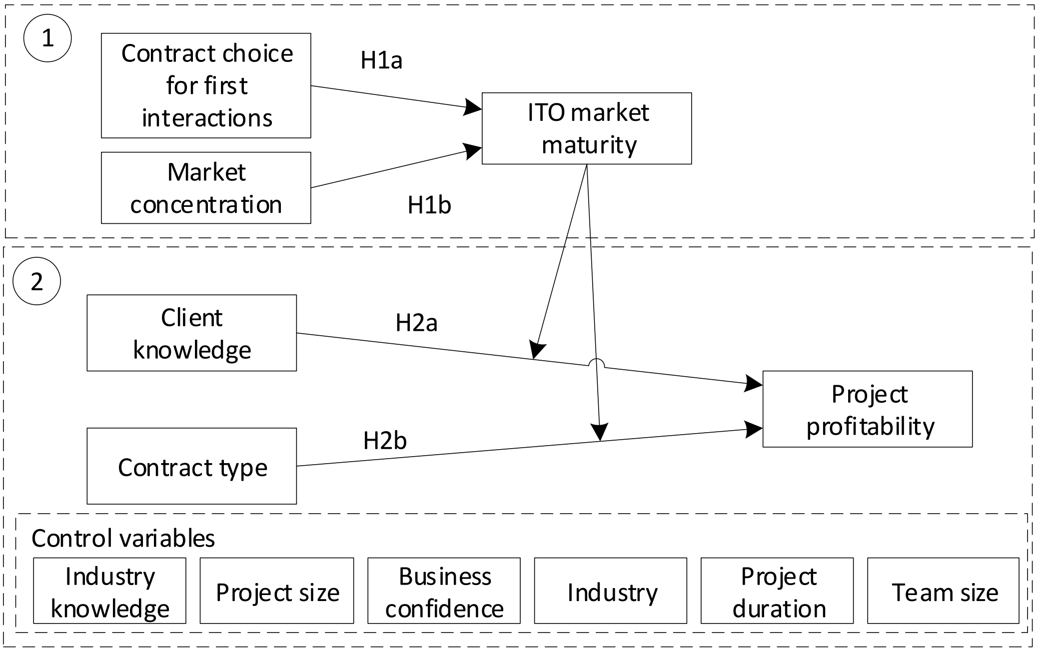

Figure 7: Research model

6.4 Research Method and Preliminary Results

We have already completed the construction of the data set which is described below. This paper focuses on the separation of the ITO market into different phases of maturity. Therefore, only hypotheses H1a and H1b are examined. Hypotheses H2a and H2b will be addressed in future research.

6.4.1 Research Site and Data Collection

In order to examine the influence of ITO market maturity on the contract choice, we collected quantitative data from ALPHA, a large German IT service provider. ALPHA generates most of its revenue through consulting projects for clients from various industries, but also offers other ITO services such as standard software development and hosting.

The data have been extracted directly from the project controlling system of ALPHA who granted us access to all 36,413 projects conducted between January 1995 and April 2014. The information on the projects is of high quality because it was extracted from the project controlling system of ALPHA, which is also used for billing clients. Additionally, directly accessing quantitative data is not subject to recall bias, which could be a problem in case studies and surveys (Gefen et al., 2008). The data set contains many variables such as the project profitability, the contract type, the team size, the number of interactions with the client as well as within the industry, the business confidence [based on the ifo index (ifo Institute, 2014)], the project start, the project size, the industry of the client and the project duration. We filtered out internal projects, removed projects with incomplete data, and applied trimming (Eriksson et al., 2006) to the project volume, project profitability, project duration and team size in order to remove outliers. This approach is commonly used in empirical ITO vendor studies to clean the data set (Hoermann et al., 2015; Schermann et al., 2014; Suarez et al., 2013). The first two years of data from the data set were removed because the first projects for a client should really be the first ones and not simply the start of the data set. The number of short projects increases towards the end of the data set as it includes only finished projects. To address this issue, the projects from 2013 and 2014 were removed to have a realistic composition of projects. The final data set contains 19,895 projects for 1,394 different clients conducted between 1997 and 2012.

6.4.2 Results for Contract Choice of the First Few Interactions between Client and Vendor

Variable	**Unit**	**Min**	**Mean**	**Max**	**SD**
Number of interaction with client	Number	1	2.25	5	1.34
Business confidence	Points	84.5	103.21	115	7.26
Team size	Number	1	3.01	63	4.32
Project duration	Days	1	194.10	3,071	317.52
Project size	Hours worked	0.5	700.70	46,268.02	2,470.16
Project start	Days since 01.01.1997	1	3,666.67	5,830	1,413.09

Table 32: Descriptive statistics

In order to examine the first few interactions, we removed projects where ALPHA and the client had more than 5 prior interactions. The created sub-data set contains 2,968 projects.

In addition to the numerical variables described in Table 32, the data set contains categorical variables. *Contract type* is measured with a binary variable, where "1" stands for a FP and "0" for a TM contract. The data set contains 785 FP and 2,183 TM contracts. The variable *Industry* denotes the industry of the client and is based on the ISIC Rev. 4 categorization (United Nations Statistics Division, 2015). The projects were conducted for clients from 17 different industries.

In order to examine the influence of ITO market maturity on the contract choice, a generalized additive model for dichotomous dependent variables with a probit link function has been used because it reveals non-linear relationships (Hastie & Tibshirani, 1990). Some of the independent variables have been log-transformed to reduce skewness (Hair et al., 2006). The variance inflation factor did not show any sign of multi-collinearity (James et al., 2013; Sachs & Hedderich, 2009). *Project start* has been included in the model as a nonparametric smoothing term. The other variables, whose linear estimates are shown in Table 33, were estimated with standard parametric methods.

Dependent variable: contract type (0 = TM, 1 = FP)		
Variable	**Estimate**	**z-Value**
(Intercept)	-0.789375	-1.783
log(Number of interaction with client)	0.039609	0.867
Business confidence	0.009966*	2.522
log(Team size)	0.456609***	10.217
log(Project duration)	-0.066257**	-3.206
log(Project size)	-0.079487***	-3.383
factor (industry) [1]	between -1.301447 and 0.420885	between 0.655 and -5.630
Significance: *** = significant at the 0.1% level; **= significant at the 1% level; *= significant at the 5% level		
[1] because of confidentiality issues the estimates for different industries are not displayed		

Table 33: Linear results of generalized additive model

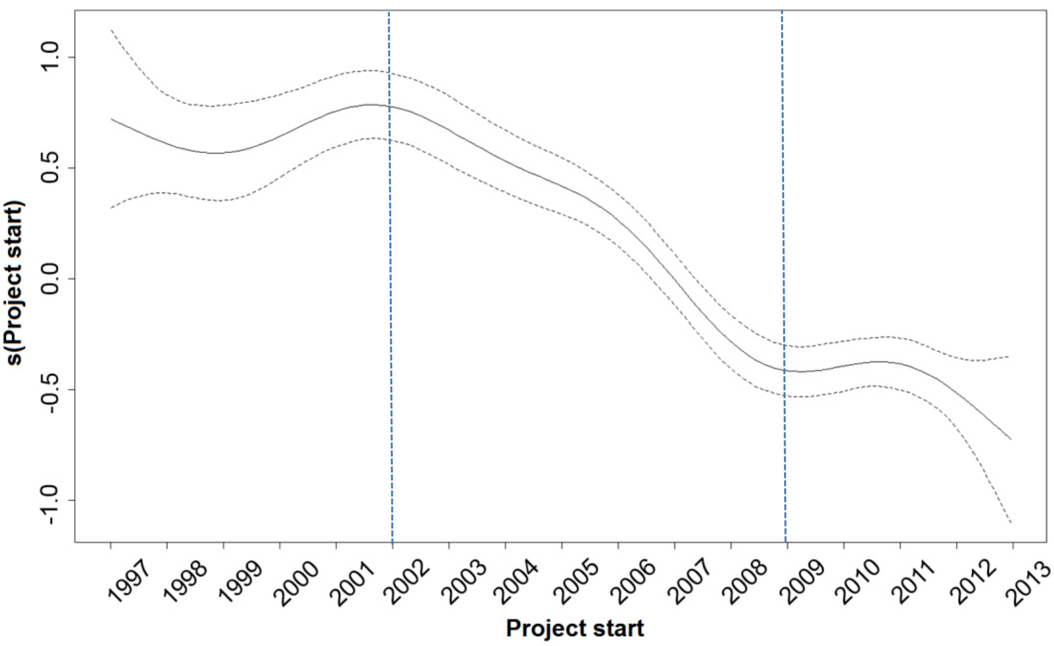

Figure 8: Probability of FP contracts for the first few interactions with the client

Figure 8 shows the non-linear plot for the variable *Project start* of the generalized additive model for dichotomous dependent variables. The dotted lines indicate the 95% significance interval. Figure 8 can be interpreted as the probability to have a FP contract for the first few vendor-client interactions. The graph shows a more or less horizontal relationship until the end of 2001 and then declines until mid-2008. There is a more or less horizontal trend until the end of 2010, then a decline; the 95% significance interval, however, widens.

6.4.3 Results for Market Concentration

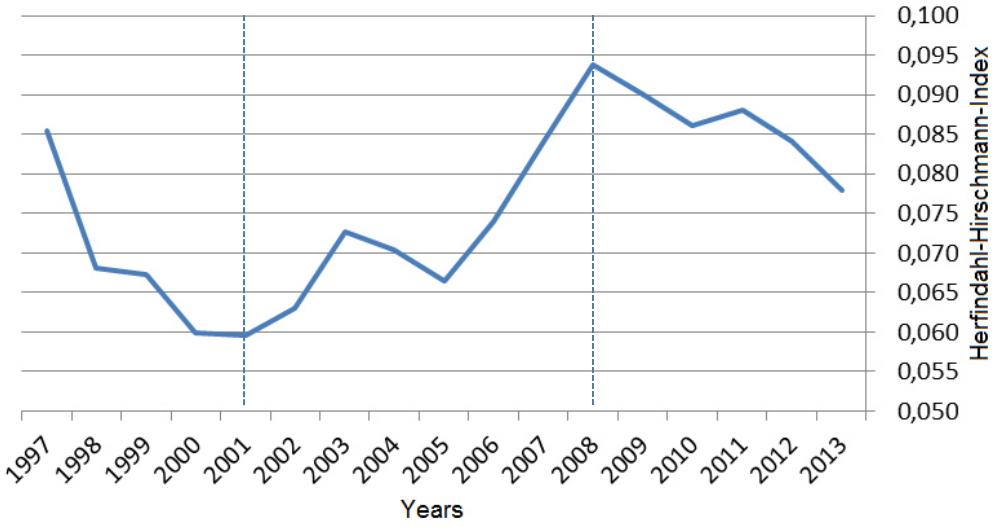

Figure 9: Market concentration of German IT consulting market

Another possibility to analyze the maturity of the ITO market is to calculate its market concentration. The German IT consulting market between 1997 and 2013 was chosen as a proxy because ALPHA is a part of it. For measuring the market concentration, the Herfindahl-Hirschmann-Index (HHI) has been used and is defined as the sum of the square of the companies' market shares (Herfindahl, 1950; Hirschman, 1945). As it is difficult to get reliable revenue figures for the entire market, a ranking of the 25 largest companies, published yearly by Lünendonk (2015), has been used as a proxy. Bailey and Boyle (1971) found that focusing on at least the eight largest companies in a market does not decrease the validity of the HHI.

For the interpretation of the market concentration, we focused on long-term trends. Therefore, we considered only trends lasting several years. The market concentration decreased from 1997 to 2001, then increased until 2008. The last few years are characterized by a slight decrease of market concentration. The results seem to indicate structural changes occurring at about years 2001 and 2008.

6.4.4 Separation of the ITO Market

Hypothesis H1a is supported. It is possible to distinguish three different phases of ITO market maturity based on the probability of having a FP contract for the first few interactions, which is a proxy for expected opportunistic behavior. The first phase lasted until the end of 2001, which is the year of separation between the immature and mature markets as defined by Susarla and Barua (2011) and Dongus et al. (2014). In this phase, the expectation of opportunistic behavior remains constant and high in comparison to the other phases. Therefore, it can be assumed that the ITO market was in an immature state until the end of 2001. The second phase occurred between 2002 and 2008 during which the expectation of opportunistic behavior continuously declined. This can be seen as a transition phase between the immature and the mature market (Klepper & Graddy, 1990). As the significance interval increases during the third phase, which started in 2009, it is not possible to determine whether the expectation of opportunistic behavior has been constant or has decreased after 2010. A constant expectation would be a sign that the ITO market has reached maturity while a decrease would argue for a second transition phase.

Hypothesis H1b is supported as well. There was a decrease in market concentration until 2001, indicative of an immature market: the market attracts new entrants which decreases the concentration (Agarwal et al., 2002; Klepper, 1996). During the following phase, which lasted until 2008, the market concentration increased. This is characteristic of a transition phase where the number of competitors decreases (Cusamano et al., 2015; Klepper & Graddy, 1990). Although in this case the market concentration decreased after 2008, in a mature market, the concentration would remain constant. This decrease is actually a sign of an immature market. Mazzucato and Semmler (1999) analyzed the market concentration of the US automobile market between 1909 and 1995. Their results indicate a high volatility of market concentration for the first decades, decreasing over time with stabilization of the market since the mid-1970s (Mazzucato & Semmler, 1999). Transferring these patterns to the ITO market indicates that the ITO market might not have yet reached maturity and still converges towards it.

As H1a and H1b indicate the same three time frames, hypothesis H1 is supported. In general, the maturity of the ITO market has increased. However, it is not clear if the ITO market is already in a mature state or if it is still in a transition phase. Klepper and Graddy (1990) have analyzed the lifecycle of several industries and found that the transition phase can last for several decades. The year 2001 has been defined as the start of the maturity of the ITO market by Susarla and Barua (2011) and Dongus et al. (2014). Our results indicate that a structural change took place, but we cannot conclude that the market is mature after 2001. Bapna et al. (2013) assumed that maturity is a continuous activity and not a certain point of time. We can support this assumption for the transition phase, but not for the other two phases. The structural change of the ITO market in 2008 has not yet been found in the literature. The financial crisis and the following economic downturn, which took place in 2008, seem to have influenced the ITO market maturity. This phenomenon calls for further research.

6.4.5 Limitations and Future Work

Before we outline our future research on the moderating effect of ITO market maturity, some limitations of our current research should be mentioned. It has been assumed that expected opportunistic behavior is especially important during the first 5 interactions between the vendor and the client. This assumption is based on an interview with a manager from ALPHA. He stated that about 5 interactions are necessary for a client to develop a trusting relationship with the vendor. He reasoned that one or two successful projects (from the viewpoint of the client) could occur because of luck, but it is unlikely that five projects are successful due to chance. In order to mitigate this limitation, models for the first one to nine interactions with a client have been constructed. The non-linear results show the same patterns.

The data used in our study comes from only one company. Therefore, the relationships we found possibly describe the maturation of this company and not of the ITO market. However, ALPHA was founded nearly two decades prior to the start of the data set and was one of the largest companies of its sector during the entire time covered by the data set. Therefore, ALPHA was presumably already a mature company at the beginning of the data set. We plan to perform the same analyses on a second data set with more than 40,000 projects from an ERP service provider. Up to now, we analyzed the market concentration of the German IT consulting market. To address this limitation, we plan to include data from other ITO market segments as well.

According to Bapna et al. (2013), multi-vendor contracting increases with ITO market maturity. From the perspective of a single vendor, this implies that the project size decreases as more vendors work on the same project. Therefore, estimating the influence of project start on the project size could be used as another indicator of market maturity.

After having shown the feasibility of separating the ITO market into different phases, we will separate the data set accordingly into sub-segments to address the hypotheses H2a and H2b in our future research. We plan to employ generalized additive models for continuous dependent variables (Hastie & Tibshirani, 1990) because the relationships between some of the independent variables and project performance are highly non-linear (Schermann et al., 2014) With the exception of Schermann et al. (2014), other studies on ITO vendor project performance have assumed linear relationships (Ethiraj et al., 2005; Gefen et al., 2008; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003). In order to answer H2a and H2b, the results for the independent variables will be compared between the different subsets.

6.5 Expected Contribution and Conclusion

We expect to contribute to theory by enhancing current knowledge of ITO market maturity. We identified three different phases of maturity with two separating structural changes. The first one, which occurred in 2001, had already been identified by Susarla and Barua (2011), but the second one, which occurred in 2008, had not yet been identified. We employed two completely different approaches to identify market maturity. The same time frames and points of structural changes have been identified. Therefore the identified phases are quite reliable. When completed, our further research on hypotheses H2a and H2b will contribute to the research stream of ITO vendor project performance. The moderating role of ITO market maturity has not yet been analyzed and should reveal new relationships.

According to our analysis of the data set, the maturity of the ITO market has increased and we identified three maturity phases occurring between 1997 and 2012. The results indicate a transition phase occurs between the immature and the mature ITO market. Up to now, this phase of the ITO market has only been considered by Stadtmann and Kreutter (2009). The question whether the ITO market is already in a mature phase could not be completely answered and will be addressed in future research.

Part B2 – Publications under Review[4]

[4] The original publications have been slightly modified, including the unification of format and reference styles, the correction of spelling errors, and minor grammatical revisions. The original version of the publications can be found in the appendix.

7. The Influence of Team and Task Familiarity within Teams on the Performance of IT Projects

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Publication	ACM SIGMIS Database
Status	Revise and Resubmit
Contribution of First Author	Problem Definition, Research Design, Data set Construction, Data Analysis, Interpretation, Reporting

Table 34. Fact Sheet Publication P2

Abstract

This paper analyzes the influence of average team familiarity, average task familiarity, distribution of team familiarity and distribution of task familiarity on the performance of IT projects. We argue that an uneven distribution of team and task familiarity leads to the formation of subgroups, which influence project performance. We conduct our analysis based on a large archive project data set. We employ random-effects regression models for our analysis. We find that average team as well as task familiarity have a positive influence on project performance. Regarding the distribution, we find that a higher concentration of team familiarity has a positive influence, but we do not find full support for the negative relationship between the concentration of task familiarity and project performance. Our results suggest that a distribution perspective in addition to an average perspective leads to additional insights when analyzing team variables such as team and task familiarity. Furthermore, we show that subgroup theory is a useful theoretical lens when analyzing the distribution of attributes within teams.

7.1 Introduction

IT projects are normally conducted by teams that are not stable over time, but are just formed for the project and only exist for the duration of the project (Huckman et al., 2009). This leads to situations where some team members might already know each other and already have worked in projects with similar tasks. The influence of team and task familiarity on IT team performance has already been analyzed by several studies (e.g. Espinosa et al. (2007) or Huckman et al. (2009)). The results show that a higher team as well as task familiarity have a positive influence on project performance.

However, these studies focus on average team and task familiarity and do not consider how the familiarity is distributed among the team members. A distribution perspective in addition to an average perspective should be taken when analyzing team variables that originate on the individual level (Kudaravalli et al., 2017; Mell, van Knippenberg, & van Ginkel, 2014). We employ subgroup theory as a theoretical lens to analyze the distribution of team and task familiarity. A subgroup is a subset of team members that is characterized by a unique form of a certain attribute (e.g. age, skill or status) (Carton & Cummings, 2012).

Previous research has found that the existence of subgroups within a team influences the performance of the team. Most studies have found a negative influence of subgroups, but some studies have argued for a positive influence (Bezrukova et al., 2009; Carton & Cummings, 2013). We argue that subgroups based on team familiarity have a positive influence, because it gives the team more structure and its members act as informal leaders. On the other hand, we argue that subgroups based on task familiarity have a negative influence, because the sharing of vital task related information is impaired. Specifically, we seek to answer the following research question: *How does the distribution of team and task familiarity among the team members influence IT project performance?* To address this research question, we conducted an empirical study with a unique quantitative data set from a German IT company. The data set covers more than 3,000 projects that have been conducted between 2000 and 2012.

We find that higher average team and task familiarity among the team members have a positive influence on project performance, which is consistent with previous literature. Additionally, our results show that a higher concentration of team familiarity increases project performance of companies, but we do not find full support for the negative influence of a higher concentration of task familiarity on IT project performance.

The remaining sections of this paper are structured as follows. First, we present background information on IT project performance, on team and task familiarity and on subgroups. This is followed by an explanation of our research model and the hypotheses that are examined are developed. We then present the research method and the found results. After mentioning the limitations of our study, there is a discussion of the identified relationships. The paper ends with possible future research and a conclusion.

7.2 Theoretical Background

7.2.1 Performance of IT Projects

IT project performance has various dimensions and different concepts exist how it can be measured. For instance, in software development projects, it is possible to use the number of defects, the deviation from the expected effort or whether the schedule was met (Huckman et al., 2009). Thomas and Fernández (2008) describe three categories with specific success criteria to judge the performance of IT projects:

- Project management: On-time, On-budget, Sponsor satisfaction, Steering group satisfaction, Project team satisfaction, Customer/user satisfaction, Stakeholder satisfaction
- Technical: System implementation, Met requirements, System quality, System use
- Business: Business continuity, Met business objectives, Delivery of benefits

If an external IT vendor is conducting the project, the performance of the IT project can be measured by the financial figures of the IT project. Previous studies have used the absolute profits of each project (Ethiraj et al., 2005; Gopal & Sivaramakrishnan, 2008; Gopal et al., 2003), the price of the contract (Gefen et al., 2008) and the profitability of the project (Hoermann et al., 2015).

The performance of IT projects is a complex construct and is influenced by many different factors (Sauer, Gemino, & Reich, 2007; Thomas & Fernández, 2008). One important factor that influence the performance of the IT project is the team and its members (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999). Each team member has different attributes, such as work history, knowledge, gender or beliefs (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999). The composition of the team influences the performance of the team (Faraj & Sproull, 2000; Huckman et al., 2009; Pelled et al., 1999).

7.2.2 Task and Team Familiarity

According to Goodman and Leyden (1991), every work place has a unique configuration and familiarity refers "to the specific knowledge a person has about these aspects of the work place". This can be related to knowledge about the task itself (task familiarity) or to knowledge about the other team members (team familiarity) (Littlepage, Robison, & Reddington, 1997).

In a setting where teams are not stable over time and constantly change, team familiarity has to be distinguished from team tenure (Cohen & Bailey, 1997; Huckman et al., 2009). In a dynamic team environment, team tenure is the time an individual belongs to the team, whereas team familiarity also considers possible relationships between individuals in previous teams (Huckman et al., 2009).

There are quite a few studies in IT as well as in non-IT context that analyze the influence of familiarity among team members on team performance (e.g. Huckman et al. (2009) or Reagans et al. (2005)). They show consistent results that team familiarity has a positive influence on the performance of the team. In literature, there are mainly two argumentations for the positive influence of team familiarity.

First, it increases the *willingness of team members to engage in group interactions*, because it increases solidarity, trust and mutual liking between the team members (Huckman et al., 2009; Petter & Carter, 2014; Ranganathan & Alfaro, 2011; Reagans et al., 2005). Additionally, familiarity decreases the uncertainty that is present while engaging in interactions within the group (Harrison, Mohammed, McGrath, Florey, & Vanderstoep, 2003; Okhuysen, 2001). A high engagement in group interactions improves communication and facilitates interpersonal as well as intergroup knowledge sharing.

Second, team familiarity *improves the coordination*, because the team members know each other's knowledge, expertise and skills (Espinosa et al., 2007; Gruenfeld, Mannix, Williams, & Neale, 1996; Huckman et al., 2009; Littlepage et al., 1997; Reagans et al., 2005). More specialized know-how can be assigned to specific tasks (He, Butler, & King, 2007; Lewis, 2004). This expertise coordination increases the team performance (Faraj & Sproull, 2000; Lewis, 2004).

Task familiarity refers to a team member's specific experience with the task that is performed within the project (Espinosa et al., 2007; Goodman & Leyden, 1991). It is a complex construct as the familiarity can refer to different aspects of the task of the IT project, such as the domain or the technology of the project (Espinosa et al., 2007).

IT as well as non-IT literature indicate that higher task familiarity has a positive influence on project performance (e.g. Espinosa et al. (2007), Harrison et al. (2003), Reagans et al. (2005) and Littlepage et al. (1997)). Repeatedly performing a task creates knowledge about the task that can be employed when performing the same or similar tasks in the future (Littlepage et al., 1997; Reagans et al., 2005). Furthermore, team members that have a higher task familiarity are better able to anticipate the impacts of their activities (Espinosa et al., 2007).

Team and task familiarity are especially important in the IT domain. First, IT projects are normally carried out in a dynamic team environment, which leads to the circumstance that IT professionals normally do not always work together with the same co-workers and work on diverse tasks (Huckman et al., 2009). Due to the changing social relationships of IT professionals and the diverse tasks that have to be performed, an IT project team consists of members with quite different degrees of team and task familiarity. Second, IT projects are often highly complex and it is necessary to closely collaborate and exchange knowledge for the successful completion of a project (Espinosa et al., 2007; He et al., 2007). This setting increases the importance of task and team familiarity within the team.

However, most studies on team and task familiarity only consider the average distribution within the team and do not consider the concentration of team and task familiarity among the team members. A rare example is Gruenfeld et al. (1996) that examine teams with different distributions of team familiarity. They compared teams of three where all members are not familiar at all, where two are familiar, but the third one is not and where all members are familiar. They found that a group that consist only of strangers perform better when the critical knowledge is evenly distributed among the team members, but groups where at least two members are familiar had a better performance, when critical knowledge was unevenly distributed. However, Gruenfeld et al. (1996) only considered teams of three and did not analyze IT teams.

7.2.3 The Emergence of Subgroups based on Team and Task Familiarity Distribution

As previously mentioned, prior research on team and task familiarity has disregarded the distribution perspective. Studies in IT literature (Kudaravalli et al., 2017) as well as in non-IT literature (Mell et al., 2014) argue that a distribution perspective should be taken when analysing attributes at the team level that originate at the individual level. If the distribution of a certain attribute is not even among the team members, false assumptions are taken when only the average is considered. Furthermore interesting insights might be missed out by only considering the average of a certain attribute. As IT professionals have diverse skills and knowledge, a distribution perspective is especially relevant when analysing IT project teams.

Subgroup theory is a useful theoretical lens when analysing the distribution of a certain attribute among members of a team. According to Carton and Cummings (2012), members of a subgroup are characterized by “a form or degree of interdependence that is unique when compared to that of other members” (p. 442). They have e.g. similar cultural values, share the same scarce resource, or possess knowledge that is unique in comparison to that shared by other members of the team (Carton & Cummings, 2012). Dividing lines, so called faultlines, that are based on attributes of diversity of team members (e.g. age, gender, knowledge or values) trigger the formation of subgroups within the same work team (Bezrukova et al., 2009; Carton & Cummings, 2012; Gibson & Vermeulen, 2003; Lau & Murnighan, 1998, 2005). Whether subgroups emerge depends on the intensity of the division by the faultline (Carton & Cummings, 2013). For example, the division between team members with an age of 40 and 50 might not be as intense as the division between members that are around 20 and 50 years old. This example is illustrated by Figure 10. The faultline divides the six team members based on their age into two subgroups. If a group is divided by faultlines, at least two subgroups emerge. Faultlines can be based either on categorical (e.g. gender or nationality) or on continuous variables (e.g. age or number of prior interactions) (Bezrukova et al., 2009; Lau & Murnighan, 1998).

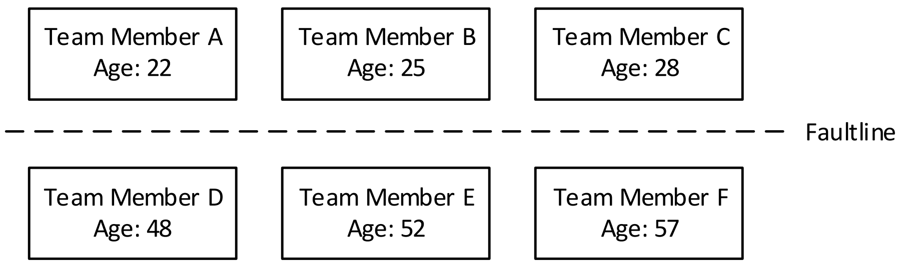


Figure 10: Example for the division of a team by a faultline

Literature distinguishes three types of subgroups (Carton & Cummings, 2012). First, members of identity-based subgroups are characterized by the same characters or share similar values (Hogg & Terry, 2000). Second, knowledge-based subgroups are formed based on technical language (Homan et al., 2007). Members of this type of subgroup often share information or use this form of exchange to solve problems and tasks together (Carton & Cummings, 2012). Third, resource-based subgroups are based on the idea of group conflict theory (Esses et al., 1998) as well as on theories of inequality and organizational ranks (Blau, 1977). Members of this type of subgroup differentiate according to the ability to claim resources, such as decision power (Carton & Cummings, 2012). Therefore, resource-based subgroups often form based on the hierarchical level.

The effects of subgroups have been studied intensively, but the empirical results differ. While some studies suggest that subgroups also have positive effects for team members (Bezrukova et al., 2009; Carton & Cummings, 2013), the majority highlights their negative consequences. In general, any type of faultline may have both, positive and negative impacts (Meyer et al., 2014). Positive effects of subgroups are mainly found related to knowledge-based subgroups (Bezrukova et al., 2009; Carton & Cummings, 2013). They have the advantage that they bring different forms of knowledge into one team (Carton & Cummings, 2013).

Negative consequences are mostly related to identity-based and resource-based subgroups. Identity-based subgroups may lead to conflicts in the whole team, caused by ethnocentrism (Cramton & Hinds, 2004; Shen, Gallivan, & Tang, 2016), especially when there are two strong subgroups of this kind in one team, which work against each other (Carton & Cummings, 2013). Resource-based subgroups in teams may lead to an asymmetry in perception of fairness and power centralization (Carton & Cummings, 2012) which disturbs the common decision making process (Sawyer et al., 2006). In general, subgroups may cause an interruption of the knowledge flow within the team, as subgroup members communicate primarily with other members of the same subgroups (Bezrukova et al., 2012). Another negative aspect is social loafing of individuals, which happens primarily in larger subgroups (Meyer et al., 2016).

We argue that the uneven distribution of task and team familiarity create faultlines that lead to the formation of subgroups. Within a project team, there might be team members that have worked together quite often in the past and therefore are quite familiar, while others hardly know each other. As project members that are familiar with each other have a higher willingness to engage in group interactions (Huckman et al., 2009; Petter & Carter, 2014; Ranganathan & Alfaro, 2011; Reagans et al., 2005), they form a subgroup.

Similarly to team familiarity, task familiarity might not be evenly distributed among the team members. There might be team members that already have performed the same or similar tasks like the ones that should be carried out during the project, while other have no experience. Team members with a high task familiarity form a subgroup, because they tend to communicate more about the task.

7.3 Research Model

Our research model can be divided into two parts. The first two hypotheses consider an average perspective and test whether relationships found in literature can be replicated. To address the call for a distribution perspective in team research (Kudaravalli et al., 2017; Mell et al., 2014), the second two hypotheses consider a distribution perspective.

As discussed, literature has found a positive influence of the average familiarity within the team on team performance. The reasoning for this relationship is that, first, the willingness to engage in group interactions is increased and, second, the coordination within the group is improved (Espinosa et al., 2007; Huckman et al., 2009). We draw on these existing findings on the influence of average team familiarity on project performance and formulate in line with existing literature the following hypothesis:

Hypothesis 1: A higher average team familiarity within the team increases project performance.

Previous research has found that task familiarity has a positive influence on project performance, because it leads to task knowledge that can be employed in the future (Espinosa et al., 2007; Reagans et al., 2005). In line with previous literature, we formulate the following hypothesis:

Hypothesis 2: A higher average task familiarity within the team increases project performance.

In comparison to others, project members with a high team familiarity form a subgroup. They know each other's expertise and are also more likely to engage in group interactions as they feel more safe (Kane et al., 2005; Reagans et al., 2005). Furthermore, team members that are not familiar with other team members align themselves with the team members that are already familiar (Gruenfeld et al., 1996). Because of this, the members of a subgroup with a high familiarity have a higher status within the team and act as informal team leaders. This formation of subgroups based on familiarity increases the team structure, which has been found to positively influence team performance (Bunderson & Boumgarden, 2010).

Whether subgroups indeed emerge depends on the intensity of the division by the faultline (Carton & Cummings, 2013). As team familiarity is a continuous variable and not a categorical, concentration increases the intensity of the division. Therefore, an increasing concentration increases the probability of the formation of subgroups. We formulate the following hypothesis:

Hypothesis 3: A higher concentration of team familiarity within the team increases project performance.

Team members with a high task familiarity form a subgroup. If subgroups exist within the team, most of the interactions occur within the subgroup (Kane et al., 2005) . Due to the imbalance of interactions between the team members, the knowledge sharing is impaired (Privman et al., 2013). The existence of subgroups can also lead to emotional conflict within the team, because the out-group can feel devalued (Derks, van Laar, & Ellemers, 2006; Pelled et al., 1999; Shen et al., 2016). If there is an imbalance regarding task familiarity within the team, the members with no or only low task familiarity need to approach the few members with a high task familiarity. This could create a bottleneck regarding the sharing of task related information.

Due to the mentioned negative influences of a high concentration of task familiarity, we formulate the following hypothesis:

Hypothesis 4: A higher concentration of task familiarity within the team decreases project performance.

7.4 Research Method

7.4.1 Research Site and Data Collection

We collected data from the internal project controlling and human resource management systems of a large German IT service provider, which is called ALPHA due to non-disclosure reasons. ALPHA is among the 10 largest IT service providers in Germany and is a company with a solid reputation in the industry. It generates most of its revenue through consulting projects, software development and large application hosting projects for clients from various industries including insurance, banking and automotive. In consulting projects and external software development projects, professionals of ALPHA typically work at the customer site, whereas they work at the offices of ALPHA during application host projects and internal software development projects.

Directly accessing quantitative data from internal systems is not subject to recall bias, which could be a problem in case studies and surveys (Espinosa et al., 2007; Gefen et al., 2008). We gathered information about each project such as project profitability, contract type, team size, number of interactions with the client, project start, project size, the industry of the client and project duration. To link each IT professional to the projects, we extracted the information which professional worked on which day for which project.

We filtered out internal projects, removed projects with incomplete data and applied trimming (Eriksson et al., 2006) to the project profitability to remove outliers, which is a common approach in empirical IT service provider studies (Hoermann et al., 2015; Schermann et al., 2014; Suarez, Cusumano, & Kahl, 2013). Projects with only one or two team members are removed, because it is not possible to consider the concentration of team familiarity properly. As the effect of task and team familiarity should be more present in larger and more intense projects, we focused on projects where the average revenue generated by each employee is at least 10.000€. This number has been chosen, because it corresponds roughly to the amount an employee generates in one month. In order to calibrate our measures for team and task familiarity, we did not consider projects that have been conducted by ALPHA between 1997 and 1999. In total, we analyzed 3,158 projects that have been conducted between 2000 and 2012.

7.4.2 Variables

7.4.2.1 Dependent Variable

There are various ways how to measure the project performance. For instance, in software development projects, it is possible to use the number of defects, the deviation from the expected effort or whether the schedule was met (Huckman et al., 2009). The performance of a project from the perspective of an IT service provider is mostly determined by the financial perspective. We have chosen the profitability of a project as the proxy for project performance, which has also been used by Hoermann et al. (2015), Gopal and Koka (2010) and Schermann et al. (2014).

7.4.2.2 Independent Variables

The four variables, in which we are interested in, are average team familiarity, average task familiarity, concentration of team familiarity and concentration of task familiarity. We see working relationships as the primary source of familiarity within IT organizations, which is consistent with other studies (Huckman et al., 2009; Reagans et al., 2005).

Average team familiarity: This variable is measured similar to the formula of Reagans et al. (2005) and Huckman et al. (2009) for measuring the familiarity within the team. The average of the number of days that each unique pair of team members have worked together is calculated.

Concentration of team familiarity: The Herfindahl-Hirschmann-Index (HHI) is a common measure for concentration. It is defined as the sum of the square of the shares of the individual observations (Herfindahl, 1950; Hirschman, 1945). This has also been employed by other studies in a similar way (Miranda, Kim, & Summers, 2015; Narayanan, Balasubramanian, & Swaminathan, 2009). The variety that we are actually measuring reflects the various possible relationships between individual team members. Because of this, we are using this index, in the sense of the HHI, as a measure for concentration.

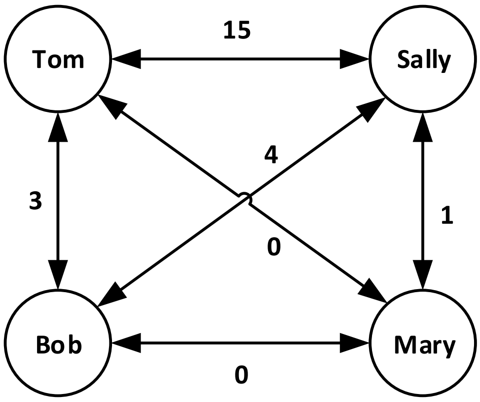
In our case, the index is defined as:

$$HHI_p = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left(\frac{interactions_{i,j,p}}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} interactions_{i,j,p}} \right)^2$$

where n is the number of team members and $interactions_{i,j}$ stands for the number of days team member i and team member j of project p have worked together. As the lower bound of the HHI decreases with an increasing number of observations, we employed the normalized HHI, which is independent of the number of distinct relationships within a group with n members $\frac{n(n-1)}{2}$ and lies between 0 and 1:

$$normalized\ HHI_p = \frac{\left(\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left(\frac{interactions_{i,j,p}}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} interactions_{i,j,p}} \right)^2 \right) - \frac{1}{\frac{n(n-1)}{2}}}{1 - \frac{1}{\frac{n(n-1)}{2}}}$$

Figure 11 illustrates the calculation of the normalized HHI for a project.



$$normalized\ HHI_p =$$

$$= \frac{\left(\frac{15}{23}\right)^2 + \left(\frac{3}{23}\right)^2 + \left(\frac{4}{23}\right)^2 + \left(\frac{1}{23}\right)^2 + \left(\frac{0}{23}\right)^2 + \left(\frac{0}{23}\right)^2 - \frac{1}{\frac{4*3}{2}}}{1 - \frac{1}{\frac{4*3}{2}}} =$$

$$= 0{,}36938$$

Figure 11: Example for calculation of normalized HHI

Average task familiarity: Repeat interactions increase the IT service provider knowledge of the client's processes, structures and technologies (Banerjee & Duflo, 2000; Chen & Bharadwaj, 2009; Mani et al., 2013). Therefore, the vendor better understands the tasks that have to be carried out during the project (Chen & Bharadwaj, 2009). This argumentation that has mainly been used on the organizational level can also be transferred to the level of individual professionals (Delaney, Reder, Staszewski, & Ritter, 1998; Huckman et al., 2009). This variable is defined as the average number of prior projects with the respective customer within the team.

Concentration of task familiarity: Similar to the concentration of team familiarity, we measure this variable with the normalized HHI. Similar to average task familiarity, the number of prior projects with the respective customer of each team member is the basis for calculating the normalized HHI.

7.4.2.3 Control Variables

We employed several control variables to filter out other factor that influence project profitability. These variables are described in the following.

Industry: ALPHA conducted projects in different industries. Competition, economic state as well as profit margin vary from industry to industry (Ethiraj et al., 2005; Hoermann et al., 2015). Because of this, the industry of the customer might have an influence on the project profitability. The industries of the customers are categorized based on the ISIC Rev. 4 (United Nations Statistics Division, 2015) and included as factors in the model.

Contract type: The two prevalent types of IT contracts are fixed-price (FP) and time and material (TM) (Gopal et al., 2003; Lichtenstein, 2004). In FP contracts, the IT service provider agrees to deliver a predefined result and is compensated with a certain fee (Ethiraj et al., 2005). TM contracts are different because the billing is based on the agreed hourly rate and the working hours invested by the IT service provider (Ethiraj et al., 2005). We include the contract type as a factor and code FP as 1 and TM as 0.

Project volume: Gopal et al. (2003), Gopal and Sivaramakrishnan (2008), Gopal and Koka (2010) and Gopal and Koka (2012) found that project volume significantly increases the absolute project profit. Ethiraj et al. (2005) argued that size increases project profitability below the minimum efficient scale and increases it above the maximum efficient scale. Additionally to the previously named studies, this variable has also been used by Hoermann et al. (2015) and Schermann et al. (2014). We employed the revenue generated by the project for approximating the project volume. To account for the skewness of this variable, we log-transformed it in our data analysis (Hair, Black, Babin, Anderson, & Tatham, 2006).

Project duration: Longer projects are harder to specify and forecast (Ethiraj et al., 2005; Gefen et al., 2008). It is also more likely that there are changes during the project (Barki, Rivard, & Talbot, 1993; Gefen et al., 2008; Nidumolu, 1995). Therefore, the performance of long running projects is lower (Sauer et al., 2007). However Hoermann et al. (2015) found that project duration increases profitability in FP projects. An explanation for this could be that it increase the time for reacting to unforeseen situations and that it is easier for the vendor to convince the client to pay higher prices (Hoermann et al., 2015). In this study, project duration is measured as the number of days that the project ran. To account for the skewness of this variable, we log-transformed it in our data analysis (Hair et al., 2006).

Team size: A large project team increases the risk of underperformance because of coordination problems (Ethiraj et al., 2005) and, hence, it might have a negative influence on the profitability of the project. However, Ethiraj et al. (2005) also argue that team size has a positive impact on profitability, in case the team is too small and, thus, overworked. In our analysis, team size is defined as the number of different employees that have worked on the project. To account for the skewness of this variable, we log-transformed it in our data analysis (Hair et al., 2006).

Start year: In order to capture any potential learning effects of ALPHA and any environmental influences, such as the overall economic situation, the start year of a project is included as a factor. This has also been done by other project performance studies (Ethiraj et al., 2005; Huckman et al., 2009).

7.4.3 Data Analysis

Table 35 and Table 36 show some descriptive statistics of numerical variables. Additionally, the data set contains 1.114 (35.3%) FP and 2.044 (64.7%) TM projects. These projects have been conducted for 227 different customers in 14 different industries. The correlation matrix can be seen in Table 36.

To test the hypotheses, we construct several multiple linear regression models. The four models each add one independent variable to the base model to test its effect. The fifth model combines the four independent variables in one regression analysis.

As our data set contains several projects for the same customer, we have to correct for panel data (Greene, 2003; Wooldridge, 2010). We conducted the Hausman tests for each model to choose between a fixed-effect and a random-effect model. The results indicated that a random-effect model should be taken for each constructed regression model. The p-values of the Hausman test for all models are clearly above 0.10.

Variable	Unit	Min	Mean	Max	SD
Project Profitability (anonymized)	%	-141.38	28.76	131.18	46.93
Team Familiarity - Average	# of prior work relationships	0.0	113.7	1111.2	116.3
Team Familiarity - Concentration	HHI	0.000	0.16	1.00	0.21
Task Familiarity – Average	# of prior projects	0.00	16.93	163.67	22.75
Task Familiarity – Concentration	HHI	0.00	0.23	1.00	0.14
Project volume	Revenue in €	30,000	340,024	21,700,000	880,986
Project duration	Days	19	327.9	4059	305.6
Team size	# of team members	3	8.43	137	9.27

Table 35: Descriptive Statistics

	1)	2)	3)	4)	5)	6)	7)	8)
1) Project profitability (anonymized)	1.00							
2) Team Familiarity – Average	0.03	1.00						
3) Team Familiarity - Concentration	0.02	-0.13 ***	1.000					
4) Task Familiarity – Average	-0.04	0.31 ***	0.07 ***	1.00				
5) Task Familiarity – Concentration	-0.003	-0.21 ***	0.20 ***	-0.11 ***	1.00			
6) log(Project volume)	0.09 ***	-0.11 ***	-0.38 ***	-0.33 ***	-0.11 ***	1.00		
7) log(Project duration)	-0.13 ***	0.05 ***	-0.07 ***	-0.05 ***	0.006	0.37 ***	1.00	
8) log(Team size)	-0.04 **	-0.10 ***	-0.49 ***	-0.13 ***	-0.20 ***	0.73 ***	0.30 ***	1.00

Table 36: Correlation Matrix

To detect multi-collinearity, we employed the variance inflation factor (VIF) (Belsley, Kuh, & Welsch, 1980; James, Witten, Hastie, & Tibshirani, 2013). The values of the VIF lie between 1 and infinity and values between 5 and 10 can be used as a threshold to decide whether a problematic amount of multi-collinearity is present or not (James et al., 2013). We obtained values below 3, which indicates that multi-collinearity should not be an issue.

7.5 Results

Table 37 shows the results of our models.

Hypothesis 1: A higher average team familiarity within the team increases project performance is supported. Model 1 and Model 5 in table 3 report a significant positive relationship between average team familiarity and project performance.

Dependent variable: Project profitability (anonymized)					
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
(Intercept)	-0.187 (0.283)	-0.169 (0.287)	-0.200 (0.282)	-0.153 (0.280)	-0.222 (0.286)
Team Familiarity - Average	0.0003 *** (0.00007)				0.0002 *** (0.00007)
Team Familiarity - Concentration			0.071 * (0.038)		0.093 ** (0.041)
Task Familiarity - Average		0.002 *** (0.0005)			0.002 *** (0.0005)
Task Familiarity – Concentration				-0.060 * (0.036)	-0.013 (0.037)
log(Project volume)	0.089 *** (0.013)	0.094 *** (0.013)	0.089 *** (0.013)	0.088 *** (0.013)	0.096 *** (0.013)
log(Project duration)	-0.097 *** (0.013)	-0.097 *** (0.013)	-0.096 *** (0.013)	-0.092 *** (0.013)	-0.102 *** (0.013)
log(Team size)	-0.139 *** (0.018)	-0.145 *** (0.018)	-0.134 *** (0.019)	-0.150 *** (0.018)	-0.128 *** (0.019)
factor(Contract type)	0.066 *** (0.018)	0.059 *** (0.018)	0.070 *** (0.018)	0.068 *** (0.018)	0.061 *** (0.018)
factor(Industry)[1]	significant	significant	significant	significant	significant
factor(Year)	significant	significant	significant	significant	significant
Adj. R-squared	9.83%	10.02%	9.53%	9.56%	10.36%
F-value	11.11 ***	11.34 ***	10.74 ***	10.78 ***	10.73
Hausman test: *Chisq* (*p-value*)	15.67 (0.55)	13.36 (0.71)	15.70 (0.55)	21.52 (0.20)	18.11 (0.58)
Significance: *** = significant at the 1% level; **= significant at the 5% level; *= significant at the 10% level, [1] because of confidentiality issues the estimates for different industries are not displayed					

Table 37: Results of regression models

Hypothesis 2: A higher average task familiarity within the team increases project performance is supported. Model 2 and Model 5 in table 3 report a significant positive relationship between average task familiarity and project performance.

Hypothesis 3: A higher concentration of team familiarity within the team increases project performance is supported. Model 3 and Model 5 in table 3 report a significant positive relationship between concentration of team familiarity and project performance.

Hypothesis 4: A higher concentration of task familiarity within the team decreases project performance is not fully supported. Whereas Model 4 in table 3 shows a significant negative relationship, Model 5 reports an insignificant negative relationship between concentration of task familiarity and project performance.

7.6 Discussion

Our results show that a higher average task familiarity as well as higher average team familiarity have a positive influence on project performance. Regarding the distribution of task and team familiarity within the project team, we find that a higher concentration of team familiarity has a positive influence on project performance. However, we do not find full support for the negative relationship between concentration of task familiarity and project performance.

7.6.1 Limitations

Our study is subject to limitations. First, we employed a data set provided by only one vendor, which might limit the generalizability. However, by choosing this approach we were able to obtain detailed quantitative data about the work history of all project members as well as detailed and reliable data on each project. Such detailed and extensive data could not be obtained through surveys or expert interviews.

A second limitation is related to the cutting of the employed data set. In order to filter-out small projects, we chose a threshold of 10.000€ revenue per professional as a minimum. To address this minimum limit, we performed robustness by choosing other values. They did not reveal substantially different relationships.

A third limitation is related to the employed proxies for team and task familiarity. Regarding the team familiarity, we only considered the familiarity of two team members and not of larger subgroups. However, studies show that people prefer to form quite small groups of only two or three members (Desportes & Lemaine, 1988; Levine & Moreland, 2008). Regarding task familiarity, by focusing on the experience with the same customer, other contributors to task familiarity are ignored. However, knowledge about the customer and the domain is crucial when conducting IT outsourcing projects (Ethiraj et al., 2005).

A fourth limitation is that our regression models only show moderate values for the adjusted R-squared. However, other studies that employed large project archive data sets did not obtain significantly higher values, when analyzing project performance (Hoermann et al., 2015; Huckman et al., 2009). We believe that the mentioned limitations do not systematically influence our results.

7.6.2 Theoretical Contribution

7.6.2.1 Average Team and Task Familiarity within the Project Team

Our findings are in line with previous literature on the influence of average team and task familiarity on IT project performance. First, we find that a higher average team familiarity positively influences project performance. This is consistent with the positive relationships found in prior studies on the influence of team familiarity in IT projects (e.g. Espinosa et al. (2007) or Huckman et al. (2009)). Higher familiarity within the team increases the willingness of the team members to engage in group interactions and improves the coordination within the team (Gruenfeld et al., 1996; Huckman et al., 2009; Reagans et al., 2005). Both aspects positively influence team processes and therefore increase project performance.

Second, we find that the average task familiarity within the project team has a positive influence on the performance, which is consistent with prior research (Banker and Slaughter (1997) or

Espinosa et al. (2007)). Huckman et al. (2009) analyzed the influence of role experience and found a positive influence. As a role is often associated with the performance of specific tasks, role experience and task familiarity can be seen as similar to some extent.

7.6.2.2 Distribution of Team and Task Familiarity within the Project Team

We extend previous research on team and task familiarity by conceptualizing their distribution among the team members. IT literature (Kudaravalli et al., 2017) as well as non-IT literature (Mell et al., 2014) has argued for taking a distribution perspective in addition to an average perspective when analysing attributes at the team level that originate at the individual level. Considering only the average perspective falls short, if team members do not have similar levels, which is the case in IT teams (Kudaravalli et al., 2017). Empirical analysis of team composition should take a broader perspective when dealing with multi-level data (Hitt, Beamish, Jackson, & Mathieu, 2007). Interesting insights are missed out by only considering average values when aggregating attributes from an individual to a project level. For instance, team A and team B have both five members and have an average task familiarity of 50 hours. However, every member of team A has a task familiarity of 50 hours whereas one member of team B has a task familiarity of 250 hours. Team A and team B will have different coordination and communication patterns, but this is not considered with an average perspective but with a distribution perspective. A similar example can be constructed for team familiarity.

We analyzed the impact of the distribution of team familiarity on project performance. Our results show that a higher concentration of familiarity increases the project performance. This indicates that it is positive to have only a few members that know each other very well. We argue that improved team structure and information sharing leads to this relationship.

First, a higher concentration of familiarity gives the team more structure, because team members that are not familiar with other team members align themselves with the team members that are already familiar (Gruenfeld et al., 1996). The team members that know each other well act as informal leaders. Our findings are in line with Bunderson and Boumgarden (2010) that argue that a higher team structure leads to more efficient team processes. Furthermore, structure within the team creates psychological safety, reduces conflicts and creates accountability as well as sense of ownership for tasks (Brown, Lawrence, & Robinson, 2005; Edmondson, 1999; Lerner & Tetlock, 1999; Pierce, Kostova, & Dirks, 2003).

Second, the presence of a small subgroup consisting of very familiar team members improves information sharing by making sure that relevant pieces of information are actually shared (Larson, Christensen, Franz, & Abbott, 1998). Mell et al. (2014) found that central team members lead to more information elaboration in the team. They act as a catalyst for information sharing and coordinate expertise. Familiar team members that form a subgroup already have meta-knowledge about each other and due to their central role in the team should develop meta-knowledge about the other team members quickly. Therefore, we argue that they act as catalyst for information sharing and coordinate the expertise within the team, which has positive impacts on team performance.

Additionally to the distribution of team familiarity, we analyzed the distribution of task familiarity, but do not find a clear picture. There are hints that a high concentration of task familiarity has a negative influence on project performance. The existence of a subgroup based on task familiarity impairs the exchange of information within the team, leads lower trust between the team members and emotional conflict (Kane et al., 2005; Pelled et al., 1999; Privman et al., 2013; Shen et al., 2016). Furthermore, a subgroup based on task familiarity can be a bottleneck regarding the information sharing, because the few members with a high task familiarity are constantly approached by the other team members that have no or low task familiarity.

However, the circumstance that we do not find a clear picture could be due to several reasons. First, the teams that we analyzed only had about eight team members, which makes it possible to easily share task knowledge between the team members. Second, agile project management methodologies, which have grown in popularity during the past years (Dybå, Dingsøyr, & Moe, 2014), rely heavily on close collaboration and regular exchange within the team. These methodologies support sharing task knowledge (Cram & Marabelli, 2018). Third, a high concentration could have positive influences, because team members with little customer knowledge prevent organizational blindness regarding the customer and bring in new insights (March, 1991).

7.6.2.3 Subgroup Theory as a Theoretical Lens

We employed subgroup theory as a theoretical lens to analyze the distribution of attributes among team members. The concept of faultlines allows describing how attributes are distributed among the team members. Carton and Cummings (2012) describe three different types of faultlines (Separation-based faultline, Disparity-based faultline, Variety-based faultline) that lead to a dominant form of one of three types of subgroups (Identity-based subgroups, Resource-based subgroups, Knowledge-based subgroups). This framework supports the analysis of the distribution of attributes among team members by providing a structure and attributes of team composition that influence team performance.

In general, the importance of team and task familiarity and of subgroups within the team will increase in the future. Agile project management frameworks, such as SCRUM, have experienced high growth rates in IT projects over the last years (Dybå et al., 2014; Tripp et al., 2016). The distribution of team familiarity is especially important in agile projects, because efficient expertise location and coordination is crucial in self-organizing project teams (Ralph & Shportun, 2013). Additionally, informal leadership, which can emerge from subgroups based on the distribution of team familiarity, can give stability to teams with no or only flat hierarchies (Bunderson & Boumgarden, 2010).

7.6.3 Practical Contribution

We contribute to practice by showing that IT project managers should consider team and task familiarity during the staffing of projects. As previously mentioned, the distribution of team familiarity is especially important in an agile project environment. We show that project managers should not only consider the average, but also the distribution of team familiarity. Ideally, the project team should consist of only a few team members that have a very high familiarity. Additionally, the average team and task familiarity should be high. However, we do not find that a specific distribution of task familiarity is beneficial.

7.6.4 Future Research

In addition to addressing the mentioned limitations, future research could analyze the distribution of other IT team related factors. As mentioned, several different subgroups exist within a team. Additionally, the formation of the different subgroups could be analyzed in more detail. This could be done with a survey or with expert interviews. In this study, we do not analyze the formation of subgroups directly, but analyze their influences on project performance.

Future research could also examine possible moderating influences of team size and project duration on the relationships found in this study. As the team and task familiarity of team members increases during the project, the effect of familiarity at the beginning of the project should be larger in shorter projects. The influence of the distribution of team familiarity could vary with team size, as the portion of the familiarity based subgroup is smaller in larger groups.

We did not distinguish whether the task of the project is more of technical or more of design nature. Kudaravalli et al. (2017) found that a centralization of team interaction is benefical in technical collaboration, but harmful in design collaboration. A similar relationship could exist for team and task familiarity

7.7 Conclusion

Our study is motivated by the lack of research on the distribution of team and task familiarity in IT projects. Based on the analysis of a large archive project data set from a German IT company, we find that a higher average team as well as task familiarity has a positive influence. Additionally, we find that a higher concentration of team familiarity has a positive influence, but we do not find full support for a negative relationship between the concentration of task familiarity and project performance.

Part C

1. Not published studies

In addition to the seven publications in part B1 and part B2, two more studies have been conducted, but have not been published.

1.1 Choice of Contract Form in IT Outsourcing: A Multi-Level Model

1.1.1 Introduction

The IT outsourcing (ITO) industry, defined as the assignment of an IT task to a vendor, is the subject of an extensive research literature (see the reviews by Lacity et al. 2010; Lacity et al. 2016). From the beginning, research has investigated a wide range of ITO tasks, including "simple data entry to software development and maintenance, data center operations and full system integration" (Apte et al., 1997, p. 289). In practice, the global ITO market has become a major industry, with revenues approaching $400bn in 2015 (Statista, 2016).

Transaction Cost Economics is the dominant analytical framework adopted in the ITO literature (Dibbern et al., 2004; Klein, 2002). Recently, the role of TCE in ITO research has become the subject of an emerging critique. Two major reviews (Karimi-Alaghehband et al., 2011; Lacity et al., 2011) and a meta-analytic review of the choice of contract form in ITO (Schermann et al., 2016) report results inconsistent with the predictions of TCE.

Karimi-Alaghehband et al. (2011) report that few studies either operationalize TCE constructs rigorously or include all of the TCE constructs. They call for a more rigorous application of TCE in ITO research. In contrast, Lacity et al. (2011) interpret the same inconsistent empirical results as evidence for the limited explanatory power of TCE in the ITO domain. They call for the development of an endogenous theory of ITO.

Schermann et al. (2016) restrict their review to the effects of uncertainty on the choice of contract form in ITO, a major construct in the TCE framework. They report two findings. One is that the operationalization of uncertainty in their meta-analysis sample has a significant effect on the strength of the TCE-based predicted relationship between uncertainty and the choice of contract form. This supports the call by Karimi-Alaghehband et al. (2011) for a more rigorous application of TCE. The other finding is that the strength of this effect has declined over time, becoming non-significant for ITO projects that begun in 2000 or later. This finding supports the call by Lacity et al. (2011) to develop a new endogenous theory of ITO.

In addition, TCE has been criticized for focusing only on individual transactions and not considering the broader picture (Aubert et al., 2012; Lacity et al., 2011). For example, Loebbecke and Huyskens (2006) report that, in addition to TCE constructs, customer strategies affect the governance of IT sourcing. Extending the TCE framework, some researchers argue for a multi-level perspective when analyzing ITO (Aubert et al., 2012; Lacity & Willcocks, 1995; Loh & Venkatraman, 1992).

Drawing on these critiques, we extend the research by Schermann et al. (2016) on the choice of contract form in two ways. Responding to the call by Karimi-Alaghehband et al. (2011), we extend the research to include the four critical TCE constructs of environmental uncertainty, behavioral uncertainty, asset specificity, and transaction frequency (Williamson, 1985). Responding to the call by Lacity et al. (2011) and Aubert et al. (2012), we model the effects on choice of contract form at the task, organization and industry level.

To test this model, we investigate a unique data set from a German ITO vendor, ALPHA. The data set contains more than 10,000 projects for over 750 clients. We find that environmental uncertainty, history of contracting, and industry significantly affect the choice of contract form. Three of the four critical TCE constructs, behavioral uncertainty, asset specificity, and transaction frequency, do not affect the choice of contract form. We conclude that a multi-level theoretical structure should be adopted for the development of an endogenous theory of ITO.

The remaining sections of this paper are structured as follows. First, we present the theoretical background of the paper and develop six hypotheses. Then, we present the research methodology, including the definitions of the constructs. The results are reported and discussed. Finally, a short conclusion is presented.

1.1.2 Theoretical Background

TCE is the dominant analytical framework adopted in ITO research (Dibbern et al., 2004; Klein, 2002). Here, we briefly review the basic principles of TCE. Then, we report the findings from three recent reviews of the weak and inconsistent effects on ITO outcomes of the TCE constructs that are the motivation for this study.

1.1.2.1 Transaction Cost Economics

The three central constructs of TCE are uncertainty, transaction frequency and asset specificity, with uncertainty partitioned into environmental uncertainty and behavioral uncertainty (Williamson, 1985). Environmental uncertainty is contingent on the lack of knowledge about the future states of the transaction environment (Susarla et al., 2009). Behavioral uncertainty is contingent on the lack of knowledge about the future behavior of the actors involved (Susarla et al., 2009).

Asset specificity is defined as the “degree to which the assets used to conduct an activity can be redeployed to alternative uses and by alternative users without sacrifice of productive value” (Williamson, 1996). In high asset specificity contexts, the party that has invested in specific assets can be held hostage by the other party (Aubert et al., 2012). Asset specificity is partitioned into site specificity (geographical site of investment), physical asset specificity (equipment and tools) and human asset specificity (employee specific knowledge) (Karimi-Alaghehband et al., 2011). Transaction frequency ranges from a single transaction to continuous transactions (Karimi-Alaghehband et al., 2011).

TCE is adopted in ITO research to investigate two decisions by the customer: Whether to outsource or not, which is known as the make-or-buy decision, and for choosing the mode of governance (Williamson, 1991). In this paper, we focus on the second decision, the choice of the governance mechanism, and, specifically, the form of contract (Schermann et al., 2016). The two prevalent forms of ITO contracts are fixed-price (FP) and time and material (TM) contracts (Gopal et al., 2003; Lichtenstein, 2004).

In FP contracts, the ITO vendor agrees to deliver a predefined result and is compensated with a fixed fee (Ethiraj et al., 2005). In TM contracts, the billing is based on the agreed hourly rate and the working hours that the ITO vendor expenses (Ethiraj et al., 2005). The cost of realigning a transaction in response to disturbances differs significantly between the two contract forms (Hoermann et al., 2015). Under TM contracts, additional costs are born by the customer. Under any FP contract, the vendor bears the additional costs.

1.1.2.2 TCE in ITO Research

Recently, three reviews (see Table 1) report weak and inconsistent findings for the predictions based on TCE (Karimi-Alaghehband et al., 2011; Lacity et al., 2011; Schermann et al., 2016). Similarly, studies in the organizational and management literature report inconsistent findings for predictions based on TCE (e.g. Carter and Hodgson 2006; David and Han 2004). In addition, Carter and Hodgson report that few studies research the three constructs of uncertainty, asset specificity and transaction frequency in the same study. This is also identified as a potential validity threat to the research in the ITO domain (Karimi-Alaghehband et al., 2011; Lacity & Khan, 2016).

Study	**Method**	**Finding**	**Conclusion**
Karimi-Alaghehband et al. (2011)	Literature review	Weak and inconsistent empirical support for TCE	ITO research should apply TCE more rigorously
Lacity et al. (2011)	Literature review	Weak and inconsistent empirical support for TCE	ITO research should develop an endogenous theory
Schermann et al. (2016)	Meta-analysis	Operationalization of uncertainty influences explanatory power; Low explanatory power of TCE from year 2000	ITO research needs a new analytical framework

Table 38: Three Reviews of TCE-based Effects in ITO Research

Karimi-Alaghehband et al. (2011) review 25 ITO papers. To address the inconsistencies, they call for a more rigorous operationalization of TCE constructs and the inclusion of all the critical TCE constructs in a study. Lacity et al. (2011) review 31 ITO papers, with a substantial overlap between their sample and the papers reviewed by

Karimi-Alaghehband et al. (2011) and Lacity et al. (2011) report similar inconsistent findings but conclude that the research on ITO has already matured to the point that an endogenous theoretical framework should be developed to replace TCE as the theoretical framework for ITO research.

Schermann et al. (2016) investigate the competing arguments by Karimi-Alaghehband et al. (2011) and Lacity et al. (2011). While both Karimi-Alaghehband et al. (2011) and Lacity et al. (2011) report simple frequency counts of consistency across studies, Schermann et al. (2016) estimate the expected size effects based on the reported effect sizes, controlled for sample size. However, Schermann et al. (2016) restrict their analysis to the choice between FP and TM contracts.

Conducting a meta-analysis of 28 studies, based on 22 data sets, Schermann et al. (2016) report that the magnitude of the relationship between uncertainty and the choice of contract is contingent on the operationalization of uncertainty. This supports the call by Karimi-Alaghehband et al. (2011) for a more rigorous application of TCE. However, Schermann et al. (2016) also find that the explanatory power of TCE constructs is non-significant for ITO projects begun in 2000 and later. Therefore, they support the call by Lacity et al. (2011) to develop an endogenous theory for future ITO research.

1.1.3 A Multi-Level Model of IT Outsourcing

Aubert et al. (2012) compare the effects on ITO governance of transaction costs and production costs. They report that production costs compared with transaction costs have a stronger effect on ITO governance. In addition, they and Lacity and Willcocks (1995) argue for a multi-level perspective in future ITO research. This approach has two advantages (Burton-Jones & Gallivan, 2007; Rousseau, 1985). One is that it avoids drawing incorrect conclusions contingent on the level of analysis. The other is that it enables the analysis of the phenomenon in a broader context.

The above discussion raises the general question of the conditions for the appropriation of a theory that has been developed in one theoretical domain to be applied in another domain (Aubert & Rivard, 2016; Lacity et al., 2011; Whetten, Felin, & King, 2009). When borrowing a theory from another domain, the underlying assumptions of the theory must be formally satisfied in the new domain and the measures of the constructs must be consistent across the domains (Aubert & Rivard, 2016; Whetten et al., 2009). For example, Erramilli and Rao (1993) argue that TCE must be modified when it is adopted to investigate ITO in service-oriented firms because of the specific characteristics present in that domain, including, for example, low asset specificity.

To contribute to the development of a general, multi-level theory of ITO, we begin by developing a multi-level model of the choice of contract form in the ITO domain. Lacity et al. (2011) suggest several constructs for inclusion in such a model, including client firm characteristics, motivation to outsource, vendor characteristics and transaction attributes. Below, we begin the development of a multi-level model of contract choice as a function of TCE task characteristics, client preferences and client industry. Six hypotheses specify the effects on the choice of contract form of the full set of TCE task level constructs, client contract history, and client industry.

1.1.3.1 TCE Effects on Contract Form

We begin by theorizing about the influence of environmental uncertainty, behavioral uncertainty, asset specificity, and transaction frequency on the choice of contract. IT projects are characterized by a high degree of uncertainty, including requirements uncertainty and technology dynamics (Anderson & Dekker, 2005; Nidumolu, 1995; Schwartz & Zozaya-Gorostiza, 2003). Critically, the contract form determines the flexibility of the transaction. For example, it is relatively easy to change requirements in a TM contract, and difficult under a FP contract (Gefen et al., 2008; Gopal et al., 2003). In addition, different types of ITO tasks differ regarding their complexity and predictability (Langer, 2007), and so require different forms of contract. Formally:

H1a: Environmental uncertainty (project type) affects the form of contract in ITO.

H1b: Environmental uncertainty (project volume) affects the form of contract in ITO.

According to Williamson (1985), behavioral uncertainty compared with environmental uncertainty is the more important component of TCE. It is used in several ITO studies to explain the ratio of TM to FP contracts over a customer's lifetime (e.g. Kalnins and Mayer (2004); Gopal et al. (2003); Gefen et al. (2008))). The critical assumption is that a vendor might act opportunistically under a TM contract and, therefore, a customer would prefer a FP contract, other things being equal.

However, such behavior would expose the vendor to a major risk. If the strategy becomes public knowledge, it would potentially destroy the vendor's reputation and may even prove fatal due to the high degree of competition in the ITO market (Dibbern et al., 2008; Dongus et al., 2014; Manning et al., 2011). The assumption is implausible and not compelling.

Instead, we expect the vendor to focus on building a good reputation in their relationships with their customers, who are the source of future business (Goles, 2001; Levina & Ross, 2003). According to Willcocks, Lacity, and Craig (2016), customers obtain the best results from outsourcing when they focus on "find[ing] a partner, not a vendor" (p. 170) and when they regard "the provider as a strategic partner rather than an opportunistic vendor" (p. 170). Accepting these arguments, we reject the arguments in the existing ITO literature (e.g. Kalnins and Mayer (2004); Gopal et al. (2003); Gefen et al. (2008))) and Williamson (1985) that argue behavioral uncertainty is the critical component of the uncertainty construct. Formally:

H2: Behavioral uncertainty has a weak or trivial effect on the form of contract in ITO.

Lacity et al. (2011) and Karimi-Alaghehband et al. (2011) report that asset specificity has a weak or trivial effect on ITO governance. This is in contrast to the strong effects of asset specificity in other theoretical domains, including the automobile, aerospace, and aluminum industries (Aubert et al., 2012; Aubert & Rivard, 2016). In ITO, all three forms of asset specificity, geographic site specificity, physical asset specificity, and human asset specificity, are low.

In general, it is assumed that asset specificity in ITO is limited to human asset specificity (Aubert & Rivard, 2016). However, IT employees are mobile and can easily work for other customers. So human asset specificity in the ITO domain is also low. While Riordan and Williamson (1985) argue that asset specificity has the strongest effect of the four TCE constructs, this is not the case in the ITO industry. Formally:

H3: Asset specificity has a weak or trivial effect on the form of contract in ITO.

High transaction frequency with the same vendor generates economies of scale in governance and contracting costs (Miranda & Kim, 2006; Nam et al., 1996). However, the effects on outcomes of transaction frequency receive limited empirical support in the ITO domain (Karimi-Alaghehband et al., 2011; Lacity et al., 2011). Formally:

H4: Transaction frequency has a weak or trivial effect on the form of contract in ITO.

1.1.3.2 Client Contract History

TCE has been criticized for not capturing the history of the relationship between the client and the vendor (Lacity et al., 2011; Levinthal & Fichman, 1988; Nam et al., 1996). The argument is that the previous relationships between the vendor and the client should be incorporated in the analytical framework when analyzing ITO. Here, we examine the role of the client's history of contracting as a proxy for the client's general preference for FP compared with TM contracts.

There are three reasons for including the client's history as a client level construct. First, it captures a major dimension of the client's ITO strategy. Clients do not change their strategy after each transaction. If they did, the choice of contract form would be tactical and not strategic. Instead, with the same vendor, clients typically follow the same strategy over several transactions. In addition, Loebbecke and Huyskens (2006) report that client strategies compared with TCE characteristics have a stronger influence on the decision to outsource.

Second, most vendor offer both forms of contract and, in a competitive market, the differential risks of the two forms would be priced into the contract. So, if the strategy has worked well in the past, why would the client change the strategy? A repeat contract is a sign of a successful relationship. In addition, a dissatisfied customer would be more likely to choose a new vendor in the highly competitive ITO marketplace than to simply change the contract form with the existing unsatisfactory vendor (Manning et al., 2011).

Third, employing the same contract form as for the previous contract decreases contracting costs, which are part of the ex-ante transaction costs (Benaroch, Lichtenstein, & Fink, 2016). The previous contract acts as a template for clauses and terms for the following contracts (Kalnins & Mayer, 2004). Standardizing the contract and making those changes that customize the contract to the client's needs, has the potential to both realize economies of scale with respect to contracting costs (Miranda & Kim, 2006) and to develop unique client benefits. Formally:

H5: History of contracting has a significant effect on the form of contract in ITO.

1.1.3.3 Industry Effects

Whether IT is a core capability differs from industry to industry (Oh, 2005; Slaughter & Ang, 1996). For example, IT is less important in the construction, materials and natural resources industry, where IT spending corresponds to about 1% of total revenue, than in the banking and financial services industry, where the IT spending is about 6% of revenue (Gartner, 2014). In the former industries, management might adopt an FP form of contract to control costs and outcomes. In the latter, management would have the expertise to intervene in the project, where necessary, and adopt a TM form of contract.

There is limited research on the effect of the industry on ITO. An exception is Aubert et al. (2012) who report that volatility in industry demand for ITO and the knowledge-based concentration of the industry affect the decision to outsource. In general, studies that analyze ITO frequently do not examine industry effects, although industry does influence the use of ITO (Qu, Pinsoneault, & Oh, 2011). This absence of research on industry effects is common in other IS research domains (Chiasson & Davidson, 2005; Crowston & Myers, 2004). For example, Chiasson and Davidson (2005) analyze the major IS journals and comment that studies of the effects of industry in IS domains is limited.

Inspecting how, in different industries, IS ranges from “nice to have” to “mission critical”, we speculate that industry has a major effect on the choice of contract form. Formally:

H6: Client industry has a significant effect on the form of contract in ITO.

1.1.3.4 Task, Client and Industry Effects

Figure 1 combines Hypotheses 1-6 in a multi-level model of the choice of contract form. At the task level, environmental uncertainty has a significant effect on the contract form (Hypothesis 1). Otherwise, we argue that the effects on contract form of the other TCE constructs, behavioral uncertainty, asset specificity, and transaction frequency, are weak or trivial.

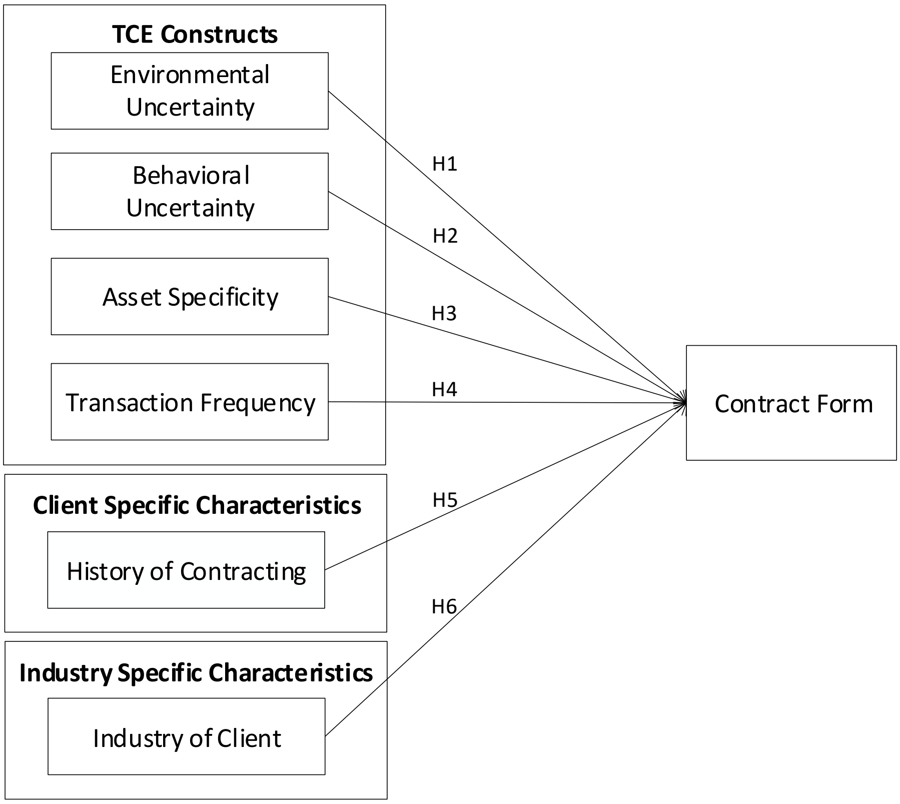


Figure 12: Research Model

Responding to the criticism by Aubert et al. (2012) and Lacity et al. (2011) of the typical transaction level model of contract form, we extend the TCE framework to include client and industry level effects. At the client level, we argue that the history of contracting between the vendor and the client has a significant effect on contract form. Why change a successful ITO strategy? (Hypothesis 5) At the industry of client level, we analyze the effect on the contract form of the client's industry, given that the importance of IT varies from one industry to another (Hypothesis 6).

1.1.4 Research Method

To address the six hypotheses developed above, we collected quantitative data from ALPHA, a large German IT service provider. Founded in the 1980s, ALPHA generates most of its revenue through consulting projects, software development and application hosting for clients from various industries, including insurance, banking and automotive. It has offices in more than 20 countries, with the majority of its business conducted in Germany, Switzerland, Austria and the USA.

The data was extracted directly from ALPHA's project control system, which is also used for billing clients and covered all 36,413 projects conducted between January 1995 and April 2014. Directly accessing quantitative data is not subject to recall bias, which is a source of a potential validity threat in case studies and surveys (Gefen et al., 2008).

We edited the data set to satisfy three criteria. First, the initial project for a customer should be the first project contracted with ALPHA. As we do not have data on projects before 1995, it is not possible to tell whether a customer is a new customer or if it is simply the first project reported in the data set. Therefore, projects before 1997 have been excluded from the data set. Second, the percentage of short projects increases towards the end of the data set because it includes only finished projects. To address this issue, projects begun after 2012 were deleted. Third, we filtered out both projects in which ALPHA was a subcontractor to another IT service provider, and projects with incomplete data.

In addition, a few customers account for a large number of projects. In the original data set, 40% of the projects have been conducted for the three largest customers. Therefore, we limited the number of projects for a single customer to the first 296 projects of that customer. This cut off value has been chosen as it limits the number of projects of the 1% largest customers. In order to address possible limitations regarding this cut off value, we performed sensitivity analyses that can be found in Appendix A. The final data set contains 10,303 projects for 775 customers.

1.1.4.1 Variables

The dependent variable is the *contract form* for each transaction. This is used by other TCE studies as a proxy for the governance mechanism (e.g. Susarla et al. (2009); Schermann et al. (2016)). We adopt the two prevalent forms of ITO contracts, namely, fixed price (FP) and time and materials (TM) contracts (Gopal et al., 2003; Hoermann et al., 2015; Lichtenstein, 2004). FP contracts are coded as 1 and TM contracts as 0.

The independent variables are environmental uncertainty, behavioral uncertainty, asset specificity, transaction frequency, client contract history, and client industry. *Environmental uncertainty* is partitioned into two constructs: *Project volume* and *project type*. These two constructs have also been used by Gopal et al. (2003), Gopal and Sivaramakrishnan (2008), Gopal and Koka (2010) and Gopal and Koka (2012) for their studies on ITO contract choice. Project volume is measured by the total hours worked on the project, and project type is based on the waterfall model, identifying five categories: *Requirements/Design, Implementation, Verification, Maintenance* and *Others*. There are 1,424 projects in the requirements/design category, 1,030 in the implementation category, 575 in the verification category, 808 in the support/maintenance category, and 6,466 were categorized as "other".

Behavioral uncertainty is coded as a zero/one variable based on the frequency with which the vendor has acted opportunistically in the recent past. Obtaining an abnormally high rate of profitability is a signal that the vendor may have acted opportunistically in the short term (Blumberg, 2001; Tonmukayakul & Weiss, 2008). To estimate this signal, the mean profitability and the standard deviation for each customer is computed. When the profitability in any one of the five previous projects is higher than the mean plus one standard deviation, the vendor is coded as exhibiting *high* uncertain behavior, and otherwise is coded as exhibiting *low* uncertain behavior.

Asset specificity is restricted to human asset specificity because site specificity and physical specific assets play only a minor role in ITO (Aubert & Rivard, 2016). Here, human asset specificity is measured as a function of specific client knowledge within the outsourcing team, with the average hours previously worked for the customer adopted as a proxy for human asset specificity. Project team members gain knowledge about the client during a project. A component of this asset is specific to each client. A similar approach is adopted by Anderson and Dekker (2005), who use training as a proxy for human asset specificity.

Transaction frequency describes a customer's activity in the market (Karimi-Alaghehband et al., 2011). Here, the number of projects with the same customer in a timeframe of +/- 180 days of a project's start is employed as a proxy for transaction frequency. While multi-vendor sourcing has become the dominant form of ITO (Dibbern et al., 2004), we assume that a high number of transactions between ALPHA and a customer is a proxy for the customer's activity in the market. We consider future projects because both the customer and the vendor would be aware of other projects that are likely to start in the immediate future. There is often a gap of several months between the initial discussion between a vendor and a client, the signing of the contract, and the start date.

History of contracting is defined as the form of contract for the previous project between the vendor and the client. The data set contains every project that has been conducted by ALPHA for each client for the covered period.

The *industry of each ALPHA customer* is categorized based on its IT intensity. This is measured as a percentage of the total revenue that the client spends on IT. Drawing on Gartner (2014), we classify three levels of client industry IT intensity: high IT expense ratio (IT spend > 4%), medium IT expense ratio (2% ≤ IT spend ≤ 4%), and low IT expense ratio (IT spend < 2%). This is similar to the classification of client industry adopted by Hoermann et al. (2015), Aubert et al. (2012), and Oh (2005). The data set contains 1,828 projects in low IT intensive industries, 4,002 in medium IT intensive industries, and 4,473 in high IT intensive industries.

Table 39 presents descriptive statistics for each variable and for the correlation matrix among the variables. Due to the high skewness of project volume, asset specificity, and transaction frequency, these variables are log-transformed (Hair et al., 2006). The associations between continuous and binary variables are calculated based on Pearson's correlation coefficient.

	Unit	Mean	SD	1)	2)	3)	4)	5)	6)	7)	8)
1) Contract form	0 = TM 1 = FP	0.29	0.45	1.00							
2) log (Environmental uncertainty - PV)	Hours worked	5.55	1.85	-0.20	1.00						
3) Behavioral uncertainty	0 = no ARR 1= ARR	0.19	0.39	0.06	-0.02	1.00					
4) log(Asset specificity)	Hours	2,232	3,568	0.05	0.23	0.02	1.00				

5) log(Transaction frequency)	#	1.37	1.08	0.08	0.14	0.01	0.37	1.00			
6) History of contracting	0 = TM 1 = FP	0.29	0.46	0.53	-0.18	0.05	0.05	0.07	1.00		
7) Environmental uncertainty - PT	categories			0.31[2]	0.06[2]	0.05[2]	0.07[2]	0.09[2]	0.17[2]	1.00	
8) Industry of customer	categories			0.35[2]	0.25[2]	0.11[2]	0.07[2]	0.06[2]	0.35[2]	0.04[1]	1.00

[1] Based on Cramer's V, [2] Based on the square root of R2 of estimation models

Table 39: Descriptive Statistics and Association Matrix

The matrix also contains values for the categorical variables, project type and client industry. The associations between these variables and the continuous and binary variables are estimated based on regression models in which the categorical variables are treated as the independent variable, and the reported r is the square root of the variance explained. The association coefficient of the two categorical variables is calculated based on Cramer's V (Rea & Parker, 2014). Both the square root of the variance explained and Cramer's V have a range between 0 and 1, and their values have a similar interpretation to the absolute value of a correlation coefficient (Cohen, 1988, 1992; Rea & Parker, 2014).

1.1.4.2 Data Analysis

According to Whetten (1989), the factors included in a theory should satisfy two criteria, comprehensiveness and parsimony. Comprehensiveness focuses on the question of whether all relevant factors are included in the theory. Parsimony calls for the exclusion of factors that add little additional value.

Due to the large sample size, trivial and spurious relationships would report significant p-values (Cohen, 1990; Sullivan & Feinn, 2012). As effect sizes are independent of the sample size (Sullivan & Feinn, 2012), we adopt critical effect sizes to determine whether a construct has a significant influence on the contract form. We employed two effect sizes as test statistics to determine whether a construct has a significant effect.

One test statistic is based on the direct association between any two variables. We adopt a cut-off value of r = 0.15 to determine whether a construct has significant explanatory power on the choice of contract form. This value corresponds to a small to medium effect size for the correlation coefficients, and for both the estimated r and Cramer's V, in Table 2 (Cohen, 1988, 1992; Rea & Parker, 2014).

The other test statistic is the absolute changes in Nagelkerke's R2 in a logistic regression model when a construct is excluded. Excluded constructs with an absolute change in Nag. R2 of less than 2.25% have a low explanatory power, equivalent to an r=0.15. This value also corresponds to a small to medium effect size (Cohen, 1988).

In total, we estimated four logistic regression models. Model 1 evaluates the explanatory power of TCE constructs for the choice of contract form (Table 3). Constructs with a low explanatory power are excluded in the subsequent models. Models 2 and 3 (Table 4) evaluate the explanatory power of the TCE constructs that have been retained, and client level and industry level constructs, respectively. Model 4 (Table 4) includes all constructs that have been found in Models 1, 2 and 3 to have significant explanatory power.

1.1.5 Results

Dependent variable: Contract form (0 = TM; 1 = FP)		
Independent Variable	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**
Intercept	0.27 (0.076)	
Environmental uncertainty - Project type	na	8.73%*
log(Environmental uncertainty - Project volume)	-0.27 (0.013)	5.79%*
Behavioral uncertainty	0.29 (0.057)	0.30%
log(Asset Specificity)	0.04 (0.007)	0.48%
log(Transaction Frequency)	0.16 (0.023)	0.62%
Nagelkerke's R2	16.79 %	
Significance *= significant Nag. R2 >2.25%, p<0.001.		

Table 40: Explanatory Power of TCE Constructs

Table 40 and Table 41 report the results of a sequence of logistic regression models to investigate the effects on the choice of contract form of TCE variables, client contract history, and the client industry. Hypothesis *H1a: Environmental uncertainty (project type) affects the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and project type is $r=0.31 > r^*=0.15$, and Table 3 reports that Nag.R2 = 8.73% > 2.25%. Similarly, Hypothesis *H1b: Environmental uncertainty (project volume) affects the form of contract in ITO*, is also supported. Table 2 reports that the correlation coefficient between contract form and project volume is r= (-) 0.20 > r*= (-) 0.15, and Table 3 reports that Nag.R2 = 5.79% > 2.25%.

Hypothesis *H2: Behavioral uncertainty has a weak or trivial effect on the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and behavioral uncertainty is $r=0.06 < r^*=0.15$, and Table 3 reports that Nag.R2 = 0.30% < 2.25%. Similarly, Hypothesis *H3: Asset specificity has a weak or trivial effect on the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and asset specificity is $r=0.05 < r^*=0.15$, and Table 3 reports that Nag.R2=0.48% < 2.25%. Hypothesis *H4: Transaction frequency has a weak or trivial effect on the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and transaction frequency is $r=0.08 < r^*=0.15$, and Table 3 shows that Nag.R2=0.62% < 2.25%.

Hypothesis *H5: History of contracting has a significant effect on the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and history of contracting is r=0.53 > r*=0.15, and Model 2 in Table 4 shows that Nag.R2 = 25.61% > 2.25%. However, Model 2 shows that, controlling for the history of contracting, environmental uncertainty (H1b: project volume) does not explain a significant proportion of the variance in contract form Nag.R2 = 1.36% < 2.25%.

Dependent variable: Contract form (0 = TM; 1 = FP)						
Independent variable	**Model 2 – EU and HCF**	**Absolute Change in Nag. R2**	**Model 3 – EU and Industry**	**Absolute Change in Nag. R2**	**Model 4 – EU, HCF and Industry**	**Absolute Change in Nag. R2**
Intercept	-0.69 (0.086)		0.75 (0.076)		-0.48 (0.090)	
Environmental uncertainty - Project type	Significant*	5.41%	Significant*	9.30%	Significant*	5.60%
log(Environmental uncertainty - Project volume)	-0.17 (0.014)	1.36%	-0.17 (0.014)	1.89%	-0.12 (0.015)	0.66%
History of contract form	2.42 * (0.054)	25.61%			2.23 * (0.055)	19.03%
Client industry			Significant*	9.49%	Significant*	2.91%
Nagelkerke's R2	40.28%		24.15%		43.19%	
Significance *= significant Nag. R2 > 2.25%, p<0.001.						

Table 41: Explanatory Power of Client and Industry Level Constructs

Hypothesis *H6: Client industry has a significant effect on the form of contract in ITO*, is supported. Table 2 reports that the correlation coefficient between contract form and client industry is r=0.29 > r*=0.15, and Model 3 in Table 4 shows that Nag.R2 = 9.49% > 2.25%. Finally, Model 4 in Table 4 shows that project type (Nag.R2 =5.60%), history of contract form (Nag.R2 =19.03%), and industry (Nag.R2 =2.91%) have significant independent effects on contract form. Model 4 in Table 4 also explains Nag.R2 = 43.19% of the variance in contract form, supporting the *multi-level model of contract form* presented in Figure 12.

1.1.6 Additional Analysis

A comparison across the models presented in Table 40 and Table 41 provides further insights into the effects of environmental uncertainty on choice of contract form. Comparing the effects of project volume on contract form across Models 1, 2 and 3, the significant effect in Table 3 (Model 1: Nag.R2 = 5.79%) is non-significant in Table 4 when controlling for client history (Model 2: Nag.R2 = 1.36% < 2.25%) and client industry (Model 3: Nag.R2 = 1.89% < 2.25%). We speculate that project size is a function of the complexity of IT systems that differ between the industries. In that case, project size would be a task or project level characteristic with a significant effect on the choice of contract form.

Comparing Model 1 and Model 3, the effect of project type is independent of the client's industry. The effect size for project type in Table 3 (Model 1: Nag.R2 = 8.73%) is non-significantly different from the effect size in Table 4, adjusting for the change between Model 1 and Model 3 in the variance explained, (Model 3: Nag.R2 = 9.30%). In contrast, comparing Model 1 and Model 2, the difference in effect sizes for project type is contingent on contracting history, controlling for the change in the variance explained by each model, (Model 1: Nag.R2 = 8.73%; Model 2: Nag.R2 = 5.41%; change in Nag.R2 = 3.32% >2.25%).

To analyze the history of contracting in more detail, we define a stable form of contract as one in which a client employs the same contract form for 90% or more of the projects. For clients with five or more projects with the vendor, 51.2% exhibit stable patterns. Approximately half of the clients do not vary their form of contract. This explains the high influence of client history of contracting on contract form (Table 2: r=0.53). TM contracts were adopted by 85% of clients that maintained a stable contract form.

1.1.7 Discussion

In the discussion, we summarize our key findings, review five limitations to those findings, and examine the implications for theory and practice. The critical implications are twofold. One is that TCE is not an appropriate analytical framework for research into ITO. The other is that a multi-level theory of ITO, including project tasks, client level constructs, and client industry, should be developed.

1.1.7.1 Findings

The results show that TCE constructs, with the exception of environmental uncertainty, do not have a significant effect on the choice of contract form in the ITO domain. This supports the argument by Lacity et al. (2011) and Schermann et al. (2016) that a new endogenous analytical framework for ITO research should be developed. A theory, in which only where only one out of four critical constructs shows consistent significant effects, does not fulfill the parsimony criterion of a theory (see Whetten (1989)).

The results also show that client preferences, as captured by the history of contract forms adopted and client industry, have significant effects on contract form. This suggests that any new endogenous theory should have a multi-level structure: the task or project level, the client level, and the industry level. A comparison of Model 1 in Table 3 and Model 4 in Table 4 supports this conclusion. Model 1, which is restricted to TCE project task constructs, explains Nag R2 = 16.79% of the variance in contract form. In contrast, Model 4, which includes project level, client level, and industry level constructs, explains Nag R2 = 43.19% of the variance.

1.1.7.2 Limitations

All research is subject to limitations. Here, we review five potential limitations to the findings. First, the data set is restricted to a single vendor. This limits the generalizability of the results. On the other hand, data from the same vendor with multiple clients controls for vendor effects, making it possible to focus on the effects on choice of contract form of the individual TCE constructs, client preferences, and industry characteristics.

Second, the proxies for the TCE constructs may not capture the full range of the TCE constructs as specified by Williamson (1985). However, the proxies employed have been used to measure TCE constructs in previous IS studies (e.g. Gefen et al. (2008); Gopal et al. (2003); Schermann et al. (2016)). Future research should expand the range of constructs investigated.

Third, there is a moderate level of correlation between transaction frequency and asset specificity. This multi-collinearity is a potential validity threat to the null findings for their effects on contract form in Table 3. However, the non-significant correlation between each of the constructs and contract form in Table 2 is evidence that the relationship between the two constructs is not the basis of a potential validity threat to the null findings in Table 3 for the effects of asset specificity and transaction frequency on the form of contract.

In the IT domain, human asset specificity is the dominant form of asset specificity (Aubert & Rivard, 2016). When transaction frequency is high, personnel involved would quickly develop specific client knowledge. In contrast, when transaction frequency between the vendor and the customer is low, employees could leave the vendor before developing high specific client knowledge because of the high turnover rates in the IT sector (Joseph et al., 2007). So, the positive relationship between asset specificity and transaction frequency is independent of the choice of contract form.

Fourth, we employ $r^*=0.15$ as the critical test statistic to determine the significance for correlations between the TCE constructs and contract form, and $R2^*=2.25\%$ as the critical test statistic for the change in Nagelkerke's R2. These values correspond to small effects (Cohen 1988; Cohen 1992; Rea and Parker 2014). In addition, the null findings reported above for the effects of TCE constructs on contract form are invariant when the test statistics are reduced to $r^*=0.10$ and $R2^*=1.00\%$. The null findings for the effects on contract form of the TCE variables, behavioral uncertainty, asset specificity and transaction frequency, are not subject to a potential validity threat contingent on the specific values of the test statistics adopted.

Fifth, the null findings for behavioral uncertainty, asset specificity and transaction frequency are subject to a potential construct validity threat. To address this issue, we conducted sensitivity analyses, in which we varied the measures for the constructs. The analyses are presented in Appendices B to D. The findings reported in the Results section are invariant across the different measures.

1.1.7.3 Implications for Theory

This paper extends the conversation by Lacity et al. (2011) critiquing the relevance of TCE for the future research in ITO. Specifically, this paper responds to the call by Lacity et al. (2016) and Karimi-Alaghehband et al. (2011) for research that simultaneously evaluates the effects of the major TCE constructs on ITO. Both reviews comment that research in the ITO area typically investigates only the effects of individual TCE constructs, limiting the evidence to critique the relevance of TCE as the appropriate framework for future analysis of ITO. Here, in addition to examining the effects on contract form of the four major TCE constructs, we extend the theoretical framework to include client and industry level effects.

The Relevance of TCE Constructs in the ITO domain

Here, we examine the effects on contract form of each of the four major TCE constructs. First, environmental uncertainty is the only TCE construct that affects the contract form. It is generally assumed that IT projects exhibit a high degree of uncertainty (Nidumolu, 1995; Schwartz & Zozaya-Gorostiza, 2003). In that case, a FP contract compared with a TM contract is less attractive, because specifying every condition upfront is expensive. In addition, there is the risk of misspecification and unexpected events, which lead to high renegotiation costs.

Second, contrary to Kalnins and Mayer (2004), Gopal et al. (2003) and Gefen et al. (2008), we find that behavioral uncertainty and, therefore, opportunistic behavior, is not relevant to the choice of the contract form. One potential explanation for this contrary finding is the time period covered by the data sets. Schermann et al. (2016) report that uncertainty had a significant effect on contract form for projects completed before 1999 but not for those begun in 2000 or later.

Given that 89.91% of the transactions in our data set occur in 2000 and later, our null finding is consistent with Schermann et al. (2016). Similarly, the significant effects reported by Kalnins and Mayer (2004) and Gopal et al. (2003) are consistent with Schermann et al. (2016) because the former analyze a data set that contains projects conducted between 1986 and 1998, and the latter analyze projects from an Indian vendor that were completed between 1995 and 1998.

Against this interpretation, Gefen et al. (2008) analyzed projects for a European bank, conducted between 2000 and 2003. However, Schermann et al. (2016) use a median split to partition the sample in their meta-analysis. Therefore, the specific date is somewhat arbitrary and the period in which behavioral uncertainty affected contract form could have included the period 2000 to 2003.

Our finding for the null effect of behavioral uncertainty on contract form is also consistent with the argument by Dibbern et al. (2008) and Dongus et al. (2014). They conclude that it is irrational for a vendor to act opportunistically in a maturing and competitive market because the threat to future business would be very high if that strategy became public knowledge. Instead, ITO vendors should build good customer reputation to retain their customer base and to attract future business (Goles, 2001; Levina & Ross, 2003). The best results from outsourcing are obtained when the vendor and the client act as partners and not as opportunistic counterparties (Willcocks et al., 2016).

Third, our findings show that asset specificity has a trivial non-significant influence on contract form. This is consistent with the reviews by Lacity et al. (2011) and Karimi-Alaghehband et al. (2011) that report ITO relationships that include asset specificity are weak and inconsistent. Against this, Riordan and Williamson (1985) argue that asset specificity has the greatest influence among the various TCE constructs.

Erramilli and Rao (1993) argue that TCE should be modified when employed in a low asset specificity context. This is the case in the ITO context because asset specificity is limited to human asset specificity (Aubert & Rivard, 2016). However, IT employees are mobile and, therefore, human asset specificity is also low. In addition, due to the high demand for ITO services, vendors can find alternative employment for their employees and therefore cannot be held hostage by the customer, further decreasing the effect of asset specificity. So, asset specificity would have a limited influence on relationships in the ITO domain.

Fourth, consistent with the literature reviews by Karimi-Alaghehband et al. (2011) and Lacity et al. (2011), we find that transaction frequency does not affect the choice of contract form in the ITO domain. One explanation is that ITO has become a routine component of the IT sourcing strategy (Lacity et al., 2010). Therefore, ITO transactions can be categorized as recurrent for most clients. This would limit the explanatory power of this TCE construct in the ITO domain.

It is important to recognize and acknowledge that the research reported in this paper is not a test of the TCE theory. Rather, it is an investigation as to whether TCE is an appropriate analytical framework for future research in ITO. With 89.91% of the transactions that we analyze occurring in 2000 and later, our findings confirm the conclusion by Schermann et al. (2016): TCE is not a valid analytical framework for the analysis of the contract form in ITO from 2000 onwards because TCE does not satisfy the parsimony criterion (see Whetten (1989)).

Toward a Multi-Level Theory of ITO

More generally, our findings support the call by Lacity et al. (2011) to develop a new endogenous theory of ITO, and, specifically, that the new theory should include project task, client, and industry level constructs. A multi-level approach would broaden the perspective, addressing the criticism of TCE that it includes only project task level constructs (Aubert et al., 2012; Lacity et al., 2011).

A multi-level approach has been advocated for a long time (see for example, Loh and Venkatraman (1992); Lacity and Willcocks (1995)) but not developed. An exception is the multi-level approach used by Aubert et al. (2012) to analyze the decision of whether to outsource. To do this, they extended the TCE framework to include the industry levels of analysis.

The findings presented above support both the extension to include additional levels of analysis as advocated by Aubert et al. (2012) and rejection of TCE as a general analytical framework. At the task level of analysis, we show that the choice of contract form is contingent on environmental uncertainty. Rather than adopting a TCE framework at this level of analysis, we reject that choice on the grounds of parsimony. Instead, our finding could be motivated directly from the literature on incomplete contracting (see, for example, Hart and Moore 1988). This would also respond to the suggestion by Lacity et al. (2011) to include analysis of contractual governance at the project level of analysis.

At the client level of analysis, the relationship between the history of contracting, which is a proxy for governance, and choice of contract form is strong r = 0.53 (see Table 39). Also, under the heading of additional analysis in the Results section above, we report a unique finding: Over 50% of clients adopt a stable choice of contract form as a component of their ITO strategy. Furthermore, 86% of these clients adopt a TM contract.

It would appear that many clients are not concerned about the potential for opportunistic vendor behavior. This is inconsistent with a critical assumption in the TCE framework. Instead of a TCE framework, an analytical framework based on project program governance would be more appropriate (see, for example, Liu, Yetton, and Sauer (2010)).

At the industry level of analysis, Aubert et al. (2012) analyze industry volatility and knowledge-based concentration. They report that industry demand and the knowledge-based concentration of the industry affect the decision to outsource. Qu et al. (2011) report that industry characteristics, including concentration and capital intensity, affect the use of ITO.

Our finding that choice of contract form is a function of industry IT intensity extends the Aubert et al. (2012) and the Qu et al. (2011) findings to the governance of ITO. Specifically, each industry has developed a dominant form of ITO contracting that depends on whether IT is a core capability that varies across industries (Oh, 2005; Slaughter & Ang, 1996).

Importantly, our findings show that task level, client level and industry level constructs are not independent (see Figure 13). Table 39 reports that the correlation between history of contract and industry of customer is r= 0.35; the correlation between project volume and industry of customer is r = 0.25; and the correlation between project type and history of contract is r = -0.18. A formal analysis and modeling of these interdependences should be the subject of future research.

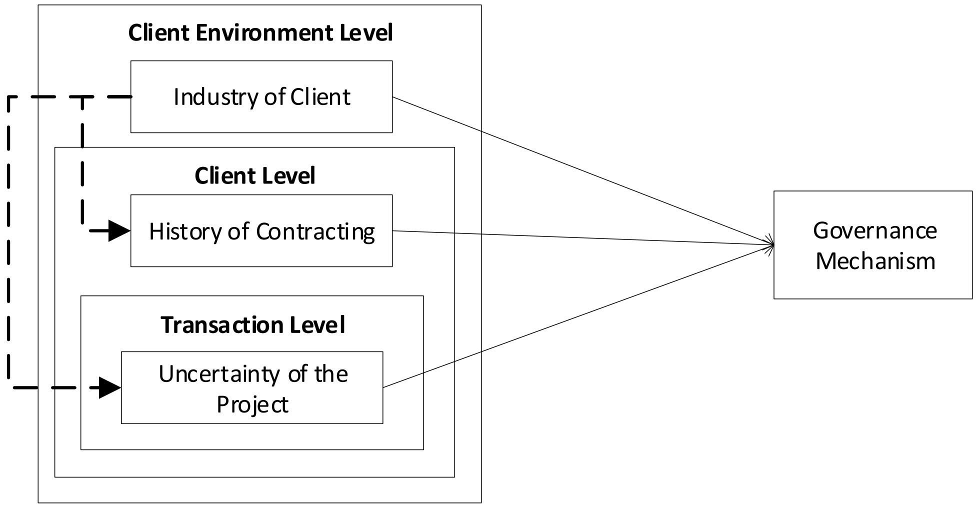


Figure 13: Multi-Level Model of Contracting in ITO

1.1.7.4 Implications for Practice

Our findings contribute to practice in three ways. First, they show that the design of an ITO contract should not be limited to a single transaction but should be treated as a component of the client's ITO strategy. The design of ITO contracts is influenced by the uncertainty of the projects, the history of contracting, and the client's industry. Therefore, ITO managers should consider these constructs when developing an ITO strategy.

Second, as the history of contracting has a large influence on the contract form of future transactions between the vendor and the client, ITO managers should carefully select the contracts for the first few interactions. A wrongly chosen contract influences not only the intended project, but also the following interactions.

Third, there is a dominant form of contracting within an industry. This is a major factor for ITO vendors when they are considering entry into a new industry. In general, vendors are able to offer and manage both forms of ITO contracts. However, there may be an initial strategic advantage by offering an alternative to the dominant contract form.

1.1.8 Conclusion

This study makes two contributions to the ongoing conversation about the applicability of TCE in ITO research. First, Karimi-Alaghehband et al. (2011) call for a more rigorous application of TCE and its constructs in ITO research. Responding to that call, we extend the Schermann et al. (2016) framework to include the four major TCE constructs. We find that environmental uncertainty affects the choice of contract form. However, the other three TCE constructs, behavior uncertainty, asset specificity, and transaction frequency, have non-significant and trivial effects on contract form. Accepting Whetten's (1989) criterion of parsimony for developing a theory, we agree with Schermann et al. (2016) that TCE is not an appropriate analytical framework for future research into ITO.

Second, we develop and test a multi-level model of contract form in ITO. Within this model, environmental uncertainty, client history of contracting, and client industry have significant effects on the choice of contract form. Together, the rejection of TCE as an appropriate analytical framework and the multi-level model of contract form, suggest that the development of new endogenous theory of ITO proposed by Lacity et al. (2011) should include task level, client level, and industry level constructs, and their relationships with ITO performance and other critical ITO dependent variables.

1.1.9 Appendix A – Alternative Cut-Off Values for Maximum Number of Interactions

A sensitivity analysis shows that the findings reported above are independent of limiting the maximum number of interactions between the customer and the vendor to 296. We calculated the correlation between contract form and the employed independent variables for the following cut off values: 20%, 40%, 60% and 80% of the original cut-off value. Table 42 shows that the findings are independent of the cut off value.

	Unit	Cut off value				
		100%	**80%**	**60%**	**40%**	**20%**
log(Environmental uncertainty - PV)	Hours worked	-0.20	-0.19	-0.18	-0.18	-0.16
Behavioral uncertainty	0 = no ARR 1= ARR	0.06	0.06	0.06	0.05	0.05
log(Asset specificity)	Hours	0.05	0.06	0.07	0.05	0.01
log(Transaction Frequency)	#	0.08	0.07	0.08	0.08	0.03
History of contracting	0 = TM 1 = FP	0.53	0.53	0.55	0.56	0.52
Environmental uncertainty - PT	Categories	0.31[1]	0.31[1]	0.31[1]	0.32[1]	0.31[1]
Industry of customer	Categories	0.35[1]	0.35[1]	0.35[1]	0.34[1]	0.29[1]

[1] Based on the square root of R2 of estimation models

Table 42: Correlation between Contract Form and the Independent Variables for Different Cut-off Values

1.1.10 Appendix B – The Measure for Behavioral Uncertainty

As outlined, behavioral uncertainty is estimated by the probability that the vendor has acted opportunistically in the recent past. Obtaining an abnormally high rate of profitability is a signal that the vendor may have acted opportunistically. To estimate this signal, the mean profitability and the standard deviation for each customer has been computed. When the profitability in anyone of the previous five projects is higher than the mean plus one standard deviation, the vendor is coded as exhibiting high uncertain behavior, and otherwise exhibiting low uncertain behavior.

An alternative measure would be to use the extent of prior interactions as a proxy for behavioral uncertainty (Gefen et al., 2008; Kalnins & Mayer, 2004). Through repetitive interactions, trust between the vendor and the customer develops and the need for safeguarding against opportunistic behavior decreases (Kalnins & Mayer, 2004).

	Behavioral uncertainty – Acted opportunistically in the past	**Log (Behavioral uncertainty – Volume of previous interactions)**
Contract form	0.06	-0.09

log(Environmental uncertainty - PV)	-0.02	0.37
log(Asset specificity)	0.02	0.41
log(Transaction frequency)	0.01	0.59
History of contracting	0.05	-0.09
Environmental uncertainty - PT	0.05[1]	0.05[1]
Industry of customer	0.11[1]	0.23[1]

[1] Based on the square root of R2 of estimation models

Table 43: Correlation between the Two Measures for Behavioral Uncertainty, the Other Independent Variables, and the Dependent Variable

Hypothesis *H2: Behavioral uncertainty has a weak or trivial effect on the form of contract in ITO*, is replicated. Table 43 reports that the correlation coefficient between contract form and behavioral uncertainty is r=(-)0.09 < r*=0.15 (instead of r=0.06 previously), and Table 44 reports that R2 = 1.46% < 2.25% (instead of R2 = 0.30%).

Dependent variable: Contract form (0 = TM; 1 = FP)				
	Behavioral uncertainty – Acted opportunistically in the past		**log (Behavioral uncertainty – Volume of previous interactions)**	
Variable	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**
Intercept	0.27 (0.076)		1.84 (0.158)	
Environmental uncertainty - Project type	na	8.73%*	na	8.47%*
log(Environmental uncertainty - Project volume)	-0.27 (0.013)	5.79%*	-0.23 (0.014)	3.62%*
Behavioral uncertainty	0.29 (0.057)	0.30%		
log(Behavioral uncertainty – Volume of previous interactions)			-0.15 (0.013)	1.46%
log(Asset specificity)	0.04 (0.007)	0.48%	0.06 (0.007)	0.86%
log(Transaction frequency)	0.16 (0.023)	0.62%	0.33 (0.028)	1.72%
Nagelkerke's R2	16.79 %		17.95 %	
Significance *= significant Nag. R2 >2.25%, p<0.001.				

Table 44: Explanatory Power of TCE Constructs

1.1.11 Appendix C – The Measure for Asset Specificity

Previously, asset specificity has been approximated by the average hours previously worked for the customer by all team members. As knowledge might lose value over time, we performed a robustness check with the average hours worked for the customer during the previous three years. Table 45 and Table 46 present the results.

	Asset specificity – average hours previously worked for the customer	**Asset specificity – average hours previously worked for the customer during last 3 years**
Contract form	0.05	0.09
log(Environmental uncertainty - PV)	0.23	0.15
Behavioral uncertainty	0.02	0.04
log(Transaction Frequency)	0.37	0.33
History of contracting	0.05	0.09
Environmental uncertainty - PT	0.07[1]	0.08[1]
Industry of customer	0.07[1]	0.10[1]

[1] Based on the square root of R2 of estimation models

Table 45: Correlation between the Two Measures for Asset Specificity and the Other Variables

Hypothesis *H3: Asset specificity has a weak or trivial effect on contract form in ITO*, is replicated for the alternative measure of asset specificity. Table 45 reports that the correlation coefficient between contract form and asset specificity is r=0.09 <r*=0.15 (instead of r=0.05 previously), and Table 46 reports that R2=1.04% < 2.25% (instead of R2=0.48% previously).

Dependent variable: Contract form (0 = TM; 1 = FP)				
	Asset specificity – average hours previously worked for the customer		**Asset specificity – average hours previously worked for the customer during last 3 years**	
Variable	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**
Intercept	0.27 (0.076)		0.09 (0.080)	
factor(Environmental uncertainty - Project type)	na	8.73%*	na	8.70% *

log(Environmental uncertainty - Project volume)	-0.27 (0.013)	5.79%*	-0.27 (0.013)	5.83% *
Behavioral uncertainty	0.29 (0.057)	0.30%	0.27 (0.058)	0.26%
log(Asset specificity)	0.04 (0.007)	0.48%		
log(Asset specificity-3 year limit)			0.08 (0.009)	1.04%
log(Transaction frequency)	0.16 (0.023)	0.62%	0.15 (0.023)	0.51%
Nagelkerke's R2	16.79 %		17.36 %	
Significance *= significant Nag. R2 >2.25%, p<0.001.				

Table 46: Explanatory Power of TCE Constructs

1.1.12 Appendix D – The Measures for Transaction Frequency

As previously outlined, transaction frequency is operationalized as the number of projects with the same customer in a timeframe of +/- 180 days of a project's start. We include future projects because both the customer and the vendor would be aware of other projects that are likely to start in the near future. There is often a gap of several months between the initial discussion between a vendor and a client, the signing of the contract, and the start date. As a robustness check, we substitute the intensity of the relationship between the customer and the vendor in that year for the number of projects, where intensity is measured by revenue from the customer in that year.

	Transaction frequency – number of projects	**Transaction frequency – intensity of relationship**
Contract form	0.08	-0.15
log(Environmental uncertainty - PV)	0.14	0.51
Behavioral uncertainty	0.01	0.60
log(Asset specificity)	0.37	0.31
History of contracting	0.07	-0.17
Environmental uncertainty – PT	0.09[1]	0.06[1]
Industry of customer	0.06[1]	0.30[1]

[1] Based on the square root of R2 of estimation models

Table 47: Correlation between the Two Measures for Transaction Frequency and the Other Variables

Hypothesis *H4: Transaction frequency has a weak or trivial effect on the form of contract in ITO*, is replicated. Table 47 reports that, while the correlation coefficient between contract form and transaction frequency is r=(-)0.15 =< r*=0.15 (compared with r=0.08 previously), Table 48 reports that Nag.R2=0.98% < 2.25% (compared with Nag.R2=0.62% previously).

Dependent variable: Contract form (0 = TM; 1 = FP)				
	Transaction frequency – number of projects		Transaction frequency – intensity of relationship	
Variable	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**	**Model 1 – TCE Constructs**	**Absolute Change in Nag. R2**
Intercept	0.27 (0.076)		1.18 (0.118)	
factor(Environmental uncertainty - Project type)	na	8.73%*	na	8.72%*
log(Environmental uncertainty - Project volume)	-0.27 (0.013)	5.79%*	-0.21 (0.116)	2.62%*
Behavioral uncertainty	0.29 (0.057)	0.30%	0.29 (0.058)	0.30%
log(Asset Specificity)	0.04 (0.007)	0.48%	0.08 (0.007)	1.68%
log(Transaction Frequency – number of projects)	0.16 (0.023)	0.62%		
log(Transaction Frequency – intensity of relationship)			-0.09 (0.011)	0.98%
Nagelkerke's R2	16.79 %		17.15 %	
Significance *= significant Nag. R2 >2.25%, p<0.001.				

Table 48: Explanatory Power of TCE Constructs

1.1.13 Appendix E – Distribution of Contracts Among Different Industries

Table 49 shows the distribution of contracts among different industries. It can be seen that the average contract in the medium IT spending industries is TM contract dominated, while the other two types use FP contracts from time to time.

IT intensity within industry	**Average contract (0=TM, 1=FP)**
High	0.4098
Medium	0.1272
Low	0.3611

Table 49: Distribution of Contracts among Different Industries

1.2 Collective Turnover: How Peer Turnover Shapes IT Professionals' Decision to Leave Their Job

1.2.1 Introduction

Turnover of professionals is a common phenomenon in the IT industry. A survey among Fortune 500 companies revealed that IT companies experience much higher turnover rates than other companies (Dishman, 2015). For several reasons, this turnover is problematic for IT organizations. First, it is difficult to find a suitable replacement due to the high demand for qualified employees in the IT labor market (Streim & Pfisterer, 2014; Thibodeau, 2012). Second, turnover creates high costs for IT organizations not only through recruiting and training, but also through the disruption of organizational processes (Chang, 2010; Sumner & Niederman, 2004; Thatcher et al., 2002). Studies estimate these costs to be between 90% and 700% of the annual salary of an IT professional (Allen et al., 2010; Kochanski & Ledford, 2001).

Research on turnover of IT professionals has a rich history in IT literature (Joseph et al., 2007; Zylka & Fischbach, 2017). It has focused on antecedents (e.g. Joseph et al. (2007), Dinger, Thatcher, Treadway, Stepina, and Breland (2015), Eckhardt, Laumer, Maier, and Weitzel (2016) or Moore (2000)) and consequences (e.g. Zylka and Fischbach (2017) or Gopal et al. (2003)) of turnover of IT professionals. Up to now, turnover of IT professionals has been studied mainly on the individual level (Naidoo, 2016).

Few studies have analyzed turnover on the collective level (e.g. Ferratt, Agarwal, Brown, and Moore (2005), Ang and Slaughter (2004) or Naidoo (2016)). Naidoo (2016), for example, observed that IT professionals leave an organization as a collective result of organizational changes. Similarly, organizational practices, such as career paths and HR practices, cause collective turnover actions within the IT organization (Ang & Slaughter, 2004; Ferratt et al., 2005).

While empirical evidence suggests that turnover on the collective level is applicable to professionals working in IT, we need a richer understanding of the movement of clusters of IT professionals. For instance, more knowledge is needed on how to mitigate the potentially higher negative consequences of clusters of turnover cases occurring within a short time period (Hancock, Allen, Bosco, McDaniel, & Pierce, 2013; Hausknecht & Trevor, 2011; Heavey, Holwerda, & Hausknecht, 2013).

In this research, we propose a collective-level theory of turnover of IT professionals that explains the movement of clusters of these professionals. Literature suggests that information on turnover spreads in organizational networks and is perceived by other co-workers as a shock event leading to an increased intention to commit turnover as well (Lee & Mitchell, 1994; Moore & Burke, 2002). Conceptualizing collective turnover as a function of the whole organizational network of an IT company is particularly important. As IT projects are normally conducted by fluid teams formed for a designated, temporary period of time, IT professionals closely collaborate with many different co-workers (Huckman & Staats, 2011; Huckman et al., 2009). Thus, an IT professional's network consists of a large number of direct as well as indirect ties with other IT professionals.

In this research we examine the emergence of collective turnover and ask, *"How does turnover spread within the organizational network of an IT company?"*

To address this research question we examine an archival data set, documenting an organizational network within one IT company. Our data set contains detailed information on more than 15,000 projects and more than 4,000 IT professionals over the course of 5 years. We use survival analysis to determine whether the probability of turnover is increased by turnover within the organizational network.

We find that turnover spreads within IT organizations. It not only spreads among current team members, but also influences former team members and indirect contacts within the organization confirming that collective turnover in the IT domain occurs in clusters. We contribute to literature on managing IT professionals by demonstrating the emergence of a turnover culture in workgroups and by showing that turnover culture spreads within IT organizations.

The remainder of this paper unfolds as follows. First, we present background information on research in IT turnover and research on collective turnover. We then outline the theoretical foundation of the turnover contagion and develop the hypotheses of this article. This is followed by our analysis and presentation of results. We then identify the implications of our work for theory and practice as well as possible future research. The paper ends with a short conclusion of the main findings.

1.2.2 Theoretical Background and Hypotheses

1.2.2.1 IT Turnover Research

Research on IT turnover has mainly focused on the antecedents and consequences of IT turnover (Zylka & Fischbach, 2017). The turnover of IT professionals has several negative consequences for an organization including high costs for training and recruitment, disruption of projects and operational processes and diminished human capital. Turnover also affects the remaining co-workers by causing employee-related problems such as poor job attitudes (Abdel-Hamid, 1989; Dess & Shaw, 2001; Pennings et al., 1998; Zylka & Fischbach, 2017). Furthermore, studies have shown that high turnover rates can increase the costs and duration of projects by up to 60 percent (Abdel-Hamid, 1989).

IS research has identified more than 43 conceptually distinct antecedents of IT turnover (Ghapanchi & Aurum, 2011; Joseph et al., 2007). Some of the more researched factors preceding turnover are job satisfaction, task-based characteristics, affective commitment, age, gender, organizational tenure or role conflict (Joseph et al., 2007). Empirical studies suggest that a combination of different antecedents add up to what is considered an individual's point of no return: the threshold that actually causes turnover behavior (Josefek & Kauffman, 2003; Niederman et al., 2007).

Various theories have been used in these studies to explain the turnover of individual professionals: organizational equilibrium theory (March & Simon, 1958), met expectations theory (Porter & Steers, 1973), linkage model (Mobley, 1977), job embeddedness theory (Mitchell & Lee, 2001) and the unfolding model of voluntary turnover (Lee & Mitchell, 1994).

1.2.2.2 The Unfolding Model of Voluntary Turnover

The unfolding model of voluntary turnover focuses on the decision process of individual voluntary turnover and posits that a shock event can trigger the decision to leave a job. The shock event can either activate a pre-existing script to quit the current employer or encourage the professional to think about the current situation and satisfaction with the employer. As thoughts of leaving the job unfold, the professional compares her/his values and goals with those of the organization. A possible mismatch of goals is called "image violation" by this theory. The unfolding model suggests two ways of acquiring a new job: either the professional actively searches for and evaluates alternatives or she/he waits for an external offer.

While the theory also considers situations without a shock event, its major contribution is the consideration of shock events as a trigger for turnover. Shock event such as personal, negative work, or job offer shocks are demonstrated to prompt leaving (Lee & Mitchell, 1994). Shock events can either be: (1) positive or negative, (2) expected or unexpected or (3) organizational or personal (Lee et al., 1999). Lee et al. (1999) suggest there are five different decision paths that are characterized by the presence of shock events: scripts, image violation, high satisfaction, search for alternative jobs and possible job offer. However, more decisions paths might exist if there are different combinations of these characteristics (Niederman et al., 2007). Niederman et al. (2007) found that IT professionals use paths that are different from those used or chosen by other occupations.

1.2.2.3 Collective Turnover of IT Professionals

While most studies on IT turnover analyze individual turnover and treat turnover events as unrelated to one another, IT turnover researchers propose shifting the focus of research to a broader relational perspective and to consider collective turnover (Moore & Burke, 2002; Naidoo, 2016). This call is consistent with turnover research in management literature, which has shifted its focus to the evaluation of collective turnover (Hausknecht, 2017; Hom, Lee, Shaw, & Hausknecht, 2017).

A small number of studies have examined collective turnover of IT professionals. Ferratt et al. (2005), for example, analyze the influence of different configurations of IT human resource management practices on turnover rates. Based on survey responses from 106 organizations, they find that a human capital focus has lower turnover rates than a task-focused configuration. Similarly, internal labor market strategies influence collective turnover rates of different IT jobs (Ang & Slaughter, 2004). IT organizations adopt different internal labor market strategies, e.g. hiring and promoting criteria, job ladders, wage systems or training procedures for different IT jobs. All these different strategies lead to different rates of collective turnover (Ang & Slaughter, 2004).

In contrast to the two quantitative studies cited above, a more recent study examined change-induced collective turnover using qualitative data (Naidoo, 2016). The author reports on a case study of a health insurance company where a group of IT professionals who were dissatisfied with the negative communication practices of their managers left the organization. While all three studies suggest a collective level turnover phenomenon, it remains unclear how collective turnover takes hold and evolves in a work team.

A culture perspective helps explain the social dynamics of workplace interactions of IT professionals and turnover (Guzman et al., 2008). Turnover culture suggests that others' attitudes and behaviors influence an individual's decision to quit in two ways (Burke & Moore, 2004; Moore & Burke, 2002). First, IT professionals perceive a co-worker's quitting as social criticism of his/her job. They use this criticism in judging their own job relatively to other jobs, which they then might perceive as better. Second, IT professionals who work in a high turnover culture likely believe that turnover is acceptable behavior (Burke & Moore, 2004) and are thus more likely to commit turnover themselves (Moore & Burke, 2002). Thereby, workplace culture affects the evolution of collective turnover in IT organizations.

The literature on organizational culture identified direction and intensity as important determinants of culture in its particular context (Cooke & Rousseau, 1988). Intensity describes the degree to which culture affects other members of a network. A great deal of the work within IT is conducted in the form of projects, which are often controlled with peer-based control mechanisms (Brhel et al., 2015; Vidgen & Wang, 2009). Particularly projects that follow an agile methodology rely on close collaboration to share knowledge (Madsen & Matook, 2010; Tang & Kishore, 2010; Vidgen & Wang, 2009). This close collaboration within IT project teams increases the intensity of cultural value including those values that encourage or lead to turnover (Burke & Moore, 2004).

Direction refers to the actual content or substance of the culture as underscored by values, behavioral norms, and thinking styles. Research on professionalism within IT suggests that IT professionals rely on self-regulation of their work (Dinger et al., 2015; Swailes, 2003). Similarly, peer-based control mechanisms such as clan control are implemented by promulgating common values, beliefs and philosophy (Chua, Lim, Soh, & Sia, 2012; Kirsch, 1997; Ouchi, 1980). These control mechanisms facilitate shared values and beliefs as a mechanism of control. In clans, shared values, norms and thinking styles alleviate the propagation of negative attitudes within the work group (Burke & Moore, 2004). While intensity and direction provide important dimensions of collective IT turnover, it remains unclear how collective turnover evolves.

A better understanding of the evolution of IT turnover culture would improve managing collective turnover from a temporal perspective. For instance, it is easier to handle the turnover of one professional per month over a 12-month period than a clustering of 12 turnover cases within one month (Nyberg & Ployhart, 2013). Finding replacements in a short time frame and keeping projects running is especially difficult for IT organizations due to the shortage of IT professionals on the job market (Streim & Pfisterer, 2014; Thibodeau, 2012). Even if a company is able to replace the IT professionals that have left, the new IT professionals need to be trained before they can work productively.

1.2.2.4 Toward an IT Turnover Contagion Theory

The central claim of this paper is that turnover spreads through the organizational network of an IT organization. A contagion metaphor can be used to illustrate this spread (Burke & Moore, 2004; Felps et al., 2009). Based on the unfolding model of voluntary turnover for IT professional and, depending on their individual job embeddedness, job satisfaction, and perceived job alternatives, we argue that receiving information about an IT turnover event in their organizational network can be a shock event that triggers further turnover.

Previous research in general management literature shows that turnover spreads in small, well-defined and co-located work groups (Feeley & Barnett, 1997; Felps et al., 2009; Krackhardt & Porter, 1986). We contextualize these previously found results to the IT domain (Hong, Chan, Thong, Chasalow, & Dhillon, 2014). The main difference between general management and IT is the unique organizational network commonly found in IT.

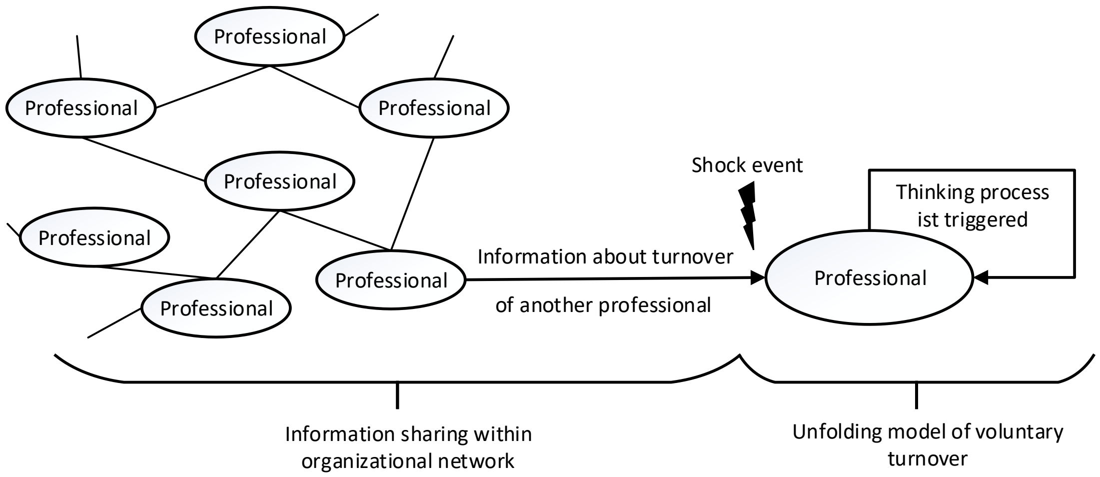


Figure 14: IT Turnover Contagion Theory

Our IT turnover contagion theory is divided into two parts (Figure 14). The first part considers the observation of the turnover by co-workers. The observability of a certain behavior is a key requirement for a contagion process (Moore & Burke, 2002; Wheeler, 1966). Observation in this case means receiving information about the planned or already committed turnover of a professional through the organizational network. While the network of IT professionals is largely a product of the nature of IT work, turnover contagion should have certain characteristics that are specific to the IT domain.

A great deal of the work within IT is conducted in the form of projects through team-based structures (Tang & Kishore, 2010). The team members rely on close collaboration to share knowledge (Madsen & Matook, 2010; Vidgen & Wang, 2009). Agile practices intensify this close collaboration (Balijepally, Mahapatra, Nerur, & Price, 2009; Hummel, Rosenkranz, & Holten, 2013). Through agile practices such as daily stand-ups or pair programming, IT professionals constantly interact informally with one another and share knowledge. Furthermore, as expertise is decentralized in agile IT projects, it becomes necessary for professionals to closely interact with co-workers and rely on their work results to succeed (Kudaravalli et al., 2017). When team members collaborate closely, they develop professional relationships that form the basis of their organizational network within the company.

Another characteristic of work in the IT sector is the strong relationship between the members of an IT project. Strong relationships develop due to the control mechanisms required for collaboration-intensive groups (Gregory & Keil, 2014). One of these control mechanisms is clan control (Chua et al., 2012). In comparison to behavior and output control, which relies on formal power and authority, clan control relies on a strong inter-personal relationship between team members. In a clan, information on values, norms, and beliefs is shared. In line with organizational culture theory, we argue that IT professionals also share negative emotions such as shock events (Burke & Moore, 2004).

IT teams are often fluid over time, i.e., they exist only for a specific duration of time, such as the time required to complete a project, and changes in the composition of the project team as IT professionals leave or join the team during the course of the project (Huckman & Staats, 2011; Huckman et al., 2009). IT professionals work together with different groups of people, thus their organizational network is diffuse and consists of many indirect contacts. This network structure enhances the sharing of information among many professionals.

Some professionals share information about their planned turnover quite early while others announce their plans at the time they actually leave (Bartunek, Huang, & Walsh, 2008; Lee, Hom, Eberly, Li, & Mitchell, 2017). Even if a professional does not talk about the turnover plan, co-workers, who work closely with that professional can spot or sense that a co-worker is in the process of leaving (Felps et al., 2009). They might observe the professional updating his resume or scheduling job interviews (Felps et al., 2009) and the close contact within teams (Vidgen & Wang, 2009) may make it difficult for the co-worker to keep any plans for turnover a secret.

Disregarding when the information on turnover is shared, there will be office talk about the turnover and its circumstances, because turnover is not a daily or routine occurrence (Bartunek et al., 2008). This spread of information about the turnover in the organizational network could be a form of workplace gossip (Foster, 2004; Grosser, Lopez-Kidwell, & Labianca, 2010; Kurland & Pelled, 2000) and is defined as "informal and evaluative talk in an organization, usually among no more than a few individuals, about another member of that organization who is not present" (Kurland & Pelled, 2000, p. 429).

The departing professional might talk about the positive aspects of the turnover, like the job perspectives and career opportunities or the wages of the new position. Within IT turnover culture research, this is referred to as "romance of turnover" (Moore & Burke, 2002). Co-workers may never know about any negative aspects of the new job. Awareness of only the positive aspects of the new job situation may influence the perception towards turnover (Moore & Burke, 2002). On the other side, professionals committing turnover often share their sentiments for the current employer with their co-workers (Bartunek et al., 2008) including feelings of anger, frustration or other negative information.

The second part of our IT turnover contagion theory focuses on the individual IT professional who is affected by the information of another professional's departure. The second important element of a contagion process is the change of perception towards a certain behavior (Wheeler, 1966). Receiving information about the turnover of another professional can be a shock (Nyberg & Ployhart, 2013). As the turnover of a co-worker is not routine, this event jars an employee to think about his/her current job situation. Based on the unfolding model of voluntary turnover, perceiving turnover information can be considered a shock event, as it has consequences for the person that trigger deliberations. Information on turnover can have positive and negative consequences. Positive consequences are information on potential job alternatives. Negative consequences can be that information on a turnover event sheds negative light on the own job and potential increased workload. Thereby, turnover information triggers a thinking process, which changes the perception of work and may ultimately result in turnover behavior (Bartunek et al., 2008).

Although extensive research exists on the antecedents of individual IT turnover, the concept of turnover contagion provides a supplementary perspective to these existing theories of turnover. It is unlikely that the contagion-based shock event is the main factor that leads to the turnover of an IT professional. The turnover intention of an IT professional, which is influenced by many different factors, can be seen as a continuum that varies over time (Josefek & Kauffman, 2003). If a certain threshold is exceeded, the respective IT professional commits turnover. Receiving information about the turnover of another IT professional might contribute to the value of the turnover intention, but also trigger a re-evaluation of the current situation.

1.2.2.5 Hypothesis development

In this paper, we analyze three different kinds of organizational networks. First, we analyze the current direct organizational network of an IT professional. This is defined as the direct relationship an IT professional (Professional 0 in Figure 15) currently has. Most of these relationships will be with other members of the project team of the IT professional (Professionals 2, 3, and 5 in Figure 15). This network is analyzed as most IT work is conducted in teams where the members collaborate closely (Tang & Kishore, 2010; Vidgen & Wang, 2009). As IT professionals closely interact with one another and depend on one another’s expertise to successfully develop and run projects, the information that a co-worker is leaving can induce a shock event.

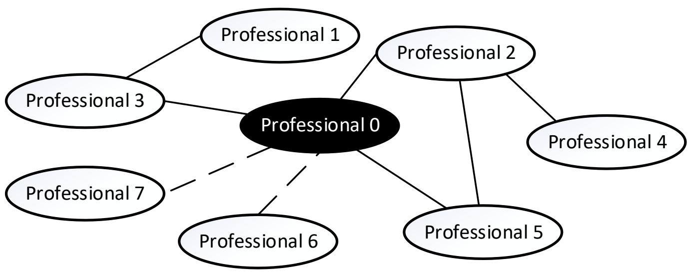


Figure 15: Different kinds of organizational networks

In the second step of our work, we analyze the past direct network. This network consists of IT professionals who have worked together in the past, but not recently. In Figure 15, the dotted lines symbolize connections among professionals who have not had a recent relationship with one another. Hence, the past direct organizational network of “Professional 0” consists of “Professional 6” and “Professional 7”. A large past direct network might be specific to the IT domain. Due to fluid teams within IT, the professionals work with one another in different team combinations over time (Huckman & Staats, 2011; Huckman et al., 2009). As a consequence, co-workers may retain close friendships even after the work relationship has ended (Kram &

Isabella, 1985; Madsen & Matook, 2010), the past direct network is influential (Kram & Isabella, 1985; Madsen & Matook, 2010).

In a third step, we analyze the current indirect network. It consists of IT professionals that do not have a direct relationship with one another but rather collaborate through an intermediary. In Figure 15, the current indirect organizational network of "Professional 0" consists of "Professional 1" and "Professional 4". Having a large number of indirect contacts might be specific to the IT context due to the structure of the organizational network. The extensively branched organizational network with a huge number of indirect ties common in IT may be a result of the fluid-team working style.

Current, Direct Organizational Network

Research suggests that turnover events affect the current, direct organizational network an IT professional is working in (Feeley & Barnett, 1997; Felps et al., 2009; Krackhardt & Porter, 1986; Naidoo, 2016). The underlying mechanism is the strong relationship the IT professionals develop with their co-workers (Burke & Moore, 2004; Chua et al., 2012). This relationship is based on the close collaboration with co-workers in teams that follow a structured development approach that involves communication and coordination (Balijepally et al., 2009; Kudaravalli et al., 2017; Vidgen & Wang, 2009).

Following our IT contagion theory, IT professionals that work on the same team are directly affected and perceive a co-workers turnover as shock event (Lee & Mitchell, 1994; Niederman et al., 2007). There are several reasons, how turnover of a co-worker affects IT professional's personal situation. First, IT professionals might fear that their direct workload might increase due to the loss of human capital (Hancock, Allen, & Soelberg, 2017). This perceived work overload can increase the likelihood of committing turnover (Ahuja, Chudoba, Kacmar, McKnight, & George, 2007). Replacing an IT professional in a team could affect the overall workload, but fundamentally change the overall work relationships within the team and day-to-day activities (Hancock et al., 2017).

Second, the departing IT professional might actively convince fellow co-workers to also leave the company. Professionals, but especially IT professionals, often maintain links with their former co-workers (Macdonald, 1986). Career-oriented social networking markets, like LinkedIn, have made this quite easy (DeKay, 2009). Research has shown that professionals find out about new jobs through personal contacts (Granovetter, 1973; Sluss & Ashforth, 2007) and many IT companies offer a referral bonus to IT professionals who have successfully recruited a co-worker who stays with the company for a designated period (Florentine, 2016). In addition, the existing work relationship reduces the uncertainty in potential performance of co-workers. This and the direct motivation through recruitment bonuses suggests that departing IT professionals recruit former team members.

In sum, IT professional's turnover creates both negative feelings and opportunities for alternative jobs for co-workers in the current, direct organizational network (Lee & Mitchell, 1994; Niederman et al., 2007). Following this line of argumentation, we suggest that the rate of turnover accelerates after the first turnover in a group. Therefore, we formulate the following first hypothesis:

H1: Turnover in the current, direct organizational network of an IT professional increases the probability of further turnover.

Past, Direct Organizational Network

In addition to the current, direct organizational network, we conceptualize the past, direct organizational network, which we understand as co-workers, an IT professional has worked with in the past, yet is not working with on the current team anymore. IT professionals develop strong personal relationships at work with high levels of trust (Kram & Isabella, 1985; Madsen & Matook, 2010). These relationships consist of friend and acquaintance relationships and require extensive time to develop, but they are stable over time (Jehn & Shah, 1997; Kram & Isabella, 1985). They are often maintained even after the work relationship has ended (Markus & Kitayama, 1991; Sluss & Ashforth, 2007). Due to the close collaboration within IT teams, especially when they are following an agile methodology, it is likely that several close friendships develop (Madsen & Matook, 2010).

Very likely, work-related information, such as co-worker turnover, is shared between former work colleagues that have become friends (Kram & Isabella, 1985). Research found that the likelihood of sharing information increases for past co-workers compared to current co-workers, because research has shown that individuals share more information with close friends than with casual friends or acquaintances (Jehn & Shah, 1997; Sias & Cahill, 1998). In addition we argue that sharing information on potential turnover, e.g. to gather feedback or job alternatives as the event would not directly affect their work situation.

However, following our IT turnover contagion argument, we argue that the information that a close friend is leaving the company is a shock event for an IT professional. Based on the unfolding model of voluntary turnover, we expect that the news of turnover triggers a thinking process in the minds of co-workers about whether to commit turnover as well (Lee & Mitchell, 1994; Niederman et al., 2007). When an IT professional has been unhappy with her/his current work situation for a longer time, steps to commit turnover may not be taken for fear of losing a friend at work (Sias & Cahill, 1998). However, if a good friend has left the work place, there is no reason for the co-worker/friend to stay at the company. In this case, turnover might snowball when the departing friend attempts to convince the left behind friend to join the new employer (Sluss & Ashforth, 2007).

Close friendships do not develop for every work relationship (Berman, West, & Richter Jr, 2002) and all co-workers are not necessarily close friends; we therefore expect a lower influence for the past, direct network than for the current, direct network. We formulate the following second hypothesis:

H2: Turnover in the past, direct organizational network of an IT professional increases the probability of turnover.

Current, Indirect Organizational Network

The spread of information within the organizational network also suggests that information about the turnover is passed on to IT professionals who do not have a direct relationship with the co-worker committing turnover. The current, indirect organizational network are all employees that are not co-workers, but are co-workers of another co-worker in the current team. We conceptualize that the spread of information about the turnover in the current, indirect organizational network is a form of workplace gossip (Foster, 2004; Grosser et al., 2010; Kurland & Pelled, 2000): the turnover of a co-worker is a notable event and is likely to cause workplace gossip. The gossip not only contains information about the turnover event, but also information about its circumstances and information on the respective professional. Research on team communication of IT professionals shows they use workplace gossip to exchange their emotions and feelings regarding other project members (Hekkala, Stein, & Rossi, 2014; Hekkala, von Hellens, & Newman, 2017). Given the criticality of a co-worker's turnover as a shock event, information on co-worker's turnover is likely to be shared as gossip through the organizational network.

The shock event might be less intense for indirect contacts because their interaction with the departing co-worker is less intimate. While they may receive information on the reasons for the turnover, because they do not know the person departing they are unable to evaluate those reasons. However, information that a colleague is departing may still trigger a thinking process among professionals not necessarily contemplating turnover. We formulate the following third hypothesis:

H3: Turnover in the current, indirect organizational network of an IT professional increases the probability of turnover.

1.2.3 Research Method

1.2.3.1 Data set

We collected data from a large German IT vendor. Due to confidentiality issues, we refer to this vendor as ALPHA. ALPHA is among the 10 largest IT outsourcing providers in Germany and is a company with a solid reputation in the industry. The company focuses on establishing and maintaining good working relationships with its professionals. Professionals stay on average about 3.8 years. During the last decade, ALPHA has pursued a growth strategy.

ALPHA generates most of its revenue through consulting projects, software development and large application hosting projects for clients from various industries including insurance, banking and automotive. In consulting projects and external software development projects, professionals of ALPHA typically work at the customer site, whereas they work at the offices of ALPHA during application host projects and internal software development projects. Projects last on average about 210 days and the typical team size is 4.4 professionals.

We employed a data set provided by ALPHA that covers the years 2008 to 2012. The data set, which has been extracted from the internal project controlling systems, contains detailed information from 15,000 projects as well as information from more than 4,000 IT professionals who worked for ALPHA during that time period. IT professionals were required to enter tasks and the corresponding project into the time recording system on a daily basis, which provided us with the complete working history of every IT professional. Therefore, we know which IT professional has worked on which day for how long for which project. As this system is used for billing hours and for calculating overtime, we have reason to believe the data is reliable. In addition to the data from the project controlling systems, we were given access to data from ALPHA's human resource management systems.

We removed IT professionals younger than 25 years of age (n=203) because they are quite often working students who leave to return to university or interns working on a limited-time contract, and professionals older than 60 (n=31) because it is likely that some of them retired and did not commit real turnover. We also excluded freelancers from the data set.

In total, the data set contains 1,403 turnover cases amongst 4,011 individual IT professionals. On average, professionals that committed turnover had worked for ALPHA for 3.7 years. The yearly turnover rate is between 10.2% and 12.3%, which corresponds to the average yearly turnover rate of a typical IT company (Scott, Klein, & Onovakpuri, 2017). The average project volume is about 1,400 hours. It should be noted that each professional works not only on one project at a time, but on average for about three projects in parallel.

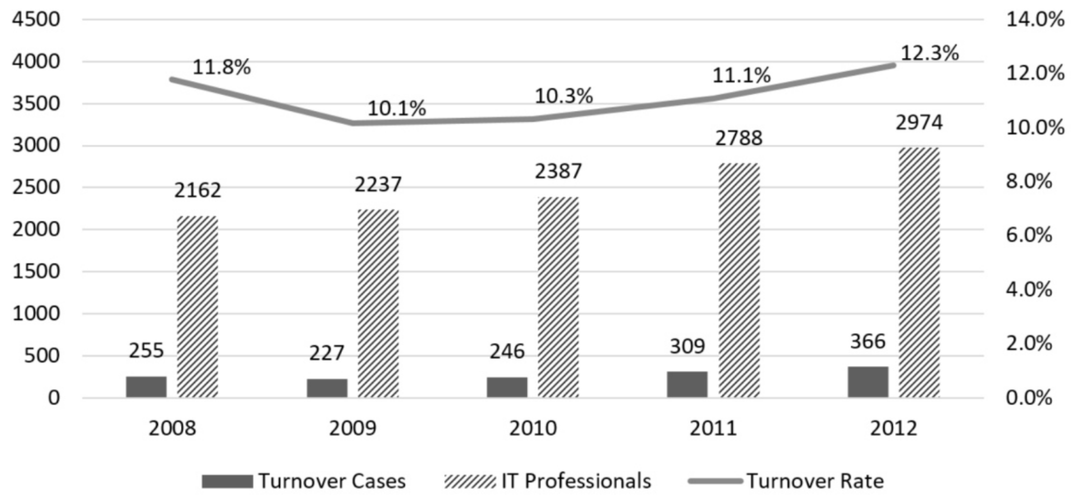


Figure 16: Number of turnover cases, number of professionals and turnover rate per year

1.2.3.2 The Organizational Network of ALPHA

As the network and its structure are crucial to our analysis, we describe both in the following. The organizational network, which we define as the set of dyadic relationships between IT professionals of the same organization, has been constructed based on the past working history of all IT professionals of ALPHA. From data on work history, we know which IT professionals have worked together on the same project and are likely to have developed a friendship (Tang & Kishore, 2010; Vidgen & Wang, 2009).

As the organizational network of an IT professional is not stable over time, we used weekly work data for our analysis. For every week under consideration, we calculate the set of persons with whom a professional has worked on the same project in the past. On average, the organizational network of a professional consists of 46 direct contacts and the number of second neighbors (contact of a contact) is 436.

The assortativity describes whether nodes with a similar degree tend to be connected with each other (Newman, 2002) and obtains values between -1 and 1. As the organizational network of ALPHA is not stable over time, we calculated the assortativity of the network for every week between the beginning of 2008 and the end of 2012. The positive average assortativity of 0.55 is typical for social networks where people tend to be connected with people similar to themselves (Newman, 2003). In our setting, being assigned to a department can intensify the assortativity of the network. We also calculated the average distance between all nodes for the different networks between 2008 and 2012 on a weekly basis. The average value of 3.31 edges shows that the network is well connected.

1.2.3.3 Strength of Turnover Influence

In the following, we describe the calculation of the strength of turnover influence. A different variable is calculated for each of the three hypotheses. We use an exemplary network (Figure 17) to illustrate the calculation of the three different strengths of turnover influence. Node “T” stands for an IT professional who committed turnover. The solid lines indicate work relationships that have taken place during the last year. The dashed lines stand for old work relationships; that is, co-workers who did not have contact with one another during the previous year. Using one year to separate current and former work relationships seemed arbitrary. We addressed this issue with robustness checks explained in the Appendix. The weight of the edges is based on the hours worked together in the past.

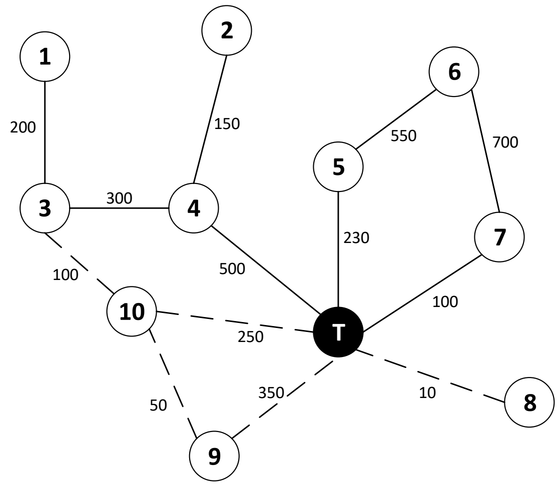


Figure 17: Exemplary organizational network

<u>Current, Direct Turnover Influence (H1)</u>

This strength of turnover influence considers whether there has been a turnover case among the direct contacts with a work relationship within the last year. In the exemplary organizational network of Figure 17, these are the nodes 4, 5 and 7. The strength of turnover influence is calculated by dividing the number of hours worked during the last year with co-worker(s) that commit turnover by the total number of hours worked with all co-workers during the last year. A similar approach was used by Feeley and Barnett (1997) for calculating their turnover social influence score. However, they only divided the number of turnover cases among direct contacts by the total number of contacts and did consider the strength of the relationship. For instance, Node 4 in the exemplary network above has a strength of turnover influence from current direct work relationships of 500/(500+300+150)=0.5263.

Past, Direct Turnover Influence (H2)

The second strength of turnover influence focuses on turnover among direct contacts without a work relationship within the last year. In the organizational network shown in Figure 17, nodes 8, 9 and 10 fulfil this requirement. The strength of turnover influence is calculated similarly as the strength of turnover influence from current, direct turnover relationships but in this case, the focus is on relationships without work-related contact within the last year. The strength of turnover influence is calculated by dividing the number of hours worked with former co-worker(s) who commit turnover by the total number of hours worked with all former co-workers. Regarding the exemplary network, node 10 has a strength of turnover influence from past, direct relationships of 250/(250+100+50)=0.6250.

Current, Indirect Influence (H3)

Current, both direct and past, direct strength of turnover influences focus on direct contacts (first neighbors). The third strength of turnover influence, current, indirect, focuses on influence from the current indirect organizational network. Because of our concern that the indirect network would get too large and undefined, we limit the indirect network to indirect contacts with only one intermediary node (second neighbors). In the example shown in Figure 17, nodes 2, 3 and 6 have a turnover case among their second neighbors. The strength of turnover influence cannot be calculated as previously because several paths between the professional that committed turnover and the influenced person can exist making it difficult to estimate the strength of turnover influence. A binary variable that indicates whether there has been a turnover case in the current, indirect network is used for this strength of turnover influence. In the exemplary organizational network above, a 1 is assigned to nodes 2, 3 and 6 and a zero is assigned to the other nodes.

Dynamic Network Analysis

The use of longitudinal data between the years 2008 and 2012 implies that the network is not stable but rather changes over time. In order to capture this dynamic, we set the unit of analysis to one week in order to capture smaller influences. We calculate the strengths of turnover influence for every professional on a weekly basis between the beginning of 2008 and the end of 2012.

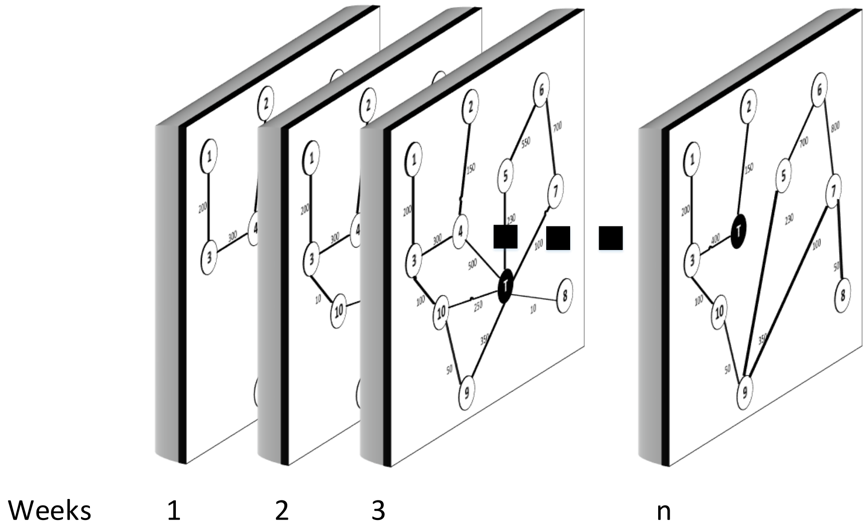


Figure 18: Dynamic network analysis on a weekly basis

As a turnover incident in the previous weeks may still influence co-workers, we employed a remembrance factor that transfers a certain amount of turnover influence to the next week. Not all of the influence is transferred because its influence diminishes over time. We have calculated this factor based on two assumptions. In the first assumption, the maximum possible turnover influence of 1 should have an influence for one year. Using one year as a lag time to analyze the influence of predictors on actual turnover is a common approach in turnover research (Griffeth, Hom, & Gaertner, 2000). According to our second assumption, the strength of turnover influence should only be transferred, and therefore remain influential, as long as it is above 5% of the average strength of turnover influence. These two assumptions lead to a remembrance factor of 88%. Hence, the strength of turnover influence consists of the influence from the previous week plus the newly acquired influence within the present week. In total, the final data set we used for the analyses contains 575,279 weekly entries for 4,011 different professionals.

1.2.3.4 Survival Analysis

We employ survival analysis to analyze the effect of turnover influence on the professionals in our data set. This method analyses the influence of external factors on the time until a certain event occurs (Martinussen & Scheike, 2006; Moore, 2016). Originally, survival analysis was used to analyze patient survival times in a medical environment, i.e. the time until death (Martinussen & Scheike, 2006, p. 1; Moore, 2016). Established as useful in medical research, survival analysis can be used to analyze the time to almost any kind of event that can be described in binary terms, i.e. either “the event happened” or “the event didn’t happen” (Morita et al., 1989, p. 280). The main benefit of survival analysis in this context is that it allows the analysis of longitudinal data and can be used to analyze whether the probability of a certain professional leaving a job increases based on a given set of covariates.

We employed Cox proportional hazard models (Cox, 1972) as they allow the usage of time dependent covariates (Martinussen & Scheike, 2006). In our case, some variables such as magnitude of turnover influence, age and business confidence, vary over time. Cox proportional hazard models also allow censored survival data (Moore, 2016). We have right- and left-censored data as there are IT professionals in the data set that had not committed turnover at the end of our observation time and there are IT professionals that had started to work before the beginning of the observation time. Lastly, we used Cox proportional hazard models because they do not require assumptions about the baseline survival distribution (Moore, 2016).

1.2.3.5 Variables

For our analyses, we employed the following variables. *Turnover* is the dependent variable in our survival analysis models. A binary variable indicates whether a certain IT professional has committed turnover in the respective week.

Strength of turnover influence from current direct relationships, *strength of turnover influence from former direct relationships* and *strength of turnover influence from current indirect relationships* are the independent variables used in our analysis. Table 50 presents an overview of the definition and the calculation of the three variables.

Variable	**Definition**	**Calculation**
Strength of turnover influence from current, direct relationships	Focuses on the direct network; considers direct contacts (first neighbors) with a work relationship within the last year.	The number of hours worked during the last year with co-worker(s) that commit turnover divided by the total number of hours worked with all co-workers during the last year.
Strength of turnover influence from former, direct relationships	Focuses on the direct network; considers direct contacts (first neighbors) without a work relationship within the last year.	The number of hours worked with former co-worker(s) that commit turnover divided by the total number of hours worked with all former co-workers.
Strength of turnover influence from current, indirect relationships	Focuses on the indirect network; considers indirect contacts within the last year with one intermediary node (second neighbors).	A binary variable that indicates whether there has been a turnover case in the current, indirect network.

Table 50: Strength of Turnover Influence

Job embeddedness is a control variable that we approximate with the network centrality of the respective IT professional (Mossholder et al., 2005). Research on turnover in management literature has shown that professionals with a low job embeddedness have a higher probability of turnover (Feeley & Barnett, 1997; Mitchell, Holtom, Lee, Sablynski, & Erez, 2001; Mossholder et al., 2005). We use the degree centrality as a measure for centrality.

Gender, a commonly used control variable in IT turnover studies, is used as a control variable in our analysis. For purposes of our analysis, gender will be used as a factor, where male IT professionals have been coded as 1 and female IT professionals as 2.

Age is used as a control variable. Several previous studies have found that turnover decreases with age (Ahuja et al., 2007; Igbaria & Guimaraes, 1993; Joseph et al., 2007; Moore, 2000). However, studies have also reported no significant influence of age on turnover (Thatcher et al., 2002; Tomer, 2015). As there might not be a linear influence of age, we coded age in 5-year ranges (26 to 30, 31 to 35, and so on) as a factor. As age data was not available for every IT professional, it was necessary to categorize the age of 2004 professionals as unknown, which corresponds to 49.5% of all IT professionals.

Unemployment rate is a control variable in our analysis. Prior IT turnover research has shown that the employment situation has a significant influence on turnover (Dinger et al., 2015; Joseph et al., 2015; Joseph et al., 2007; Thatcher et al., 2002). It is a measure for the competition between IT professionals on the job market. Unemployment rates were obtained from the German Federal Statistics Office (Statistisches Bundesamt, 2017).

Business confidence is used, similarly to the unemployment rate, as a control variable for the general economic situation. However, it is a measure for the willingness of the companies to create new jobs and to expand. The unemployment rate is a coincident indicator for the economic situation, whereas the business confidence is a leading indicator (Moore, 1984). We employed the leading German business confidence index, the ifo business climate index, which is published on a monthly basis (CES ifo Group, 2017), for this calculation.

Dominant industry of projects is used as a control variable for the situation of the project. It has been found that different industries have quite different turnover rates (Scott et al., 2017). In our study, this variable describes the dominant industry of the projects in which the IT professional participated. As the professionals work closely with the customer, they could be influenced by the industry of the customer.

Dominant contract type is used as another control variable for the project situation. It is used as a proxy for stress and pressure within the projects. Fix-price projects are more intense than time-and-material projects due to the necessity to deliver according to specifications (Gopal et al., 2003). The projects have been categorized as either fix-price, time-and-material or internal.

Success of projects is used as a third control variable for the project situation of the IT professional and is meant to capture whether an IT professional is currently experiencing project failure. It has been shown that project failures evoke negative emotions, such as frustration, disappointment, depression, anger or doubts about one’s work and subsequently increase the probability of turnover (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). This variable is defined as the average profitability of the projects for which the IT professional worked during that week.

Department size is used as a control variable for capturing the organizational situation of the IT professional. Previous research has found that department size has a significant influence on turnover (Felps et al., 2009). The number of professionals of ALPHA working at the same time for the same customer approximates this variable. As a professional might be working on several projects at the same time and these projects are not necessarily for the same customer, we focused on the dominant customer.

1.2.3.6 Descriptive Statistics

	Mean	SD	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)
1) Turnover	0.002	0.05	1.00									
2) Strength of turnover influence from current, direct relationships	0.01	0.04	0.02 ***	1.00								
3) Strength of turnover influence from former, direct relationships	0.004	0.02	0.001	0.02 ***	1.00							
4) Strength of turnover influence from current, indirect relationships	0.88	0.32	-0.001	0.13 ***	0.07 ***	1.00						
5) Job embeddedness	46.32	54.49	-0.01 ***	0.01 ***	0.02 ***	0.30 ***	1.00					
6) Gender	1.22	0.42	-0.001	-0.01 ***	-0.008 ***	-0.02 ***	-0.04 ***	1.00				
7) Business confidence	103.2	8.59	0.00	-0.03 ***	-0.04 ***	0.004 ***	0.05 ***	-0.005 ***	1.00			
8) Unemployment rate	7.44	0.66	-0.006 ***	-0.03 ***	0.01 ***	-0.02 ***	-0.10 ***	0.00	-0.41 ***	1.00		
9) Success of projects	-0.19	2.2	0.00	-0.02 ***	0.009 ***	-0.03 ***	0.009 ***	0.02 ***	0.02 ***	-0.04 ***	1.00	
10) Size of customer projects	1353	989.3	0.00	-0.02 ***	-0.02 ***	-0.01 ***	0.05 ***	0.08 ***	0.04 ***	-0.16 ***	0.08 ***	1.00

Table 51: Descriptive Statistics

Table 51 shows the mean, the standard deviation and the correlation of the numerical variables of the data set used for the survival analysis. We also used several categorical variables in our analysis. Age was categorized into seven 5-year ranges: 26 to 30 years (666 professionals), 31 to 35 (659 professionals), 36 to 40 (589 professionals), 41 to 45 (605 professionals), 46 to 50 (433 professionals), 51 to 55 (259 professionals), 56 to 60 (128 professionals). The overall average age was 38.7 years. The 15,289 conducted projects were categorized into nine different industry groups: Internal (5,103 projects), Automotive (3,650 projects), Banking (2,317 projects), Insurance (2,796 projects), Information & Communication (368 projects), Manufacturing (307 projects), Public (273 projects), Utility (97 projects), Other industries (358 projects). Contract type was grouped into Fix-Price (3,941 projects), Time-and-Material (6,934 projects) and Internal Project (4,394 projects).

1.2.4 Results

Variables	Base model	Model 1	Model 2	Model 3	Model 4
Strength of turnover influence from current, direct relationships		3.16 *** (0.27)			2.95 *** (0.28)
Strength of turnover influence from former, direct relationships			1.95 ** (0.86)		1.57 * (0.93)
Strength of turnover influence from current, indirect relationships				0.52 *** (0.09)	0.44 *** (0.09)
Job embeddedness	-0.001 * (0.0006)	-0.0009 (0.0006)	-0.001 * (0.0006)	-0.002 *** (0.0007)	-0.002 *** (0.0007)
Factor(gender)	Insignificant	Insignificant	Insignificant	Insignificant	Insignificant
Factor(age)	Significant	Significant	Significant	Significant	Significant
Business confidence	-0.006 * (0.003)	-0.005 (0.003)	-0.006 (0.003)	-0.005 (0.003)	-0.005 (0.003)
Unemployment rate	-0.43 *** (0.05)	-0.42 *** (0.05)	-0.43 *** (0.05)	-0.43 *** (0.05)	-0.42 *** (0.05)
Factor(dominant industry)	Significant	Significant	Significant	Significant	Significant
Factor(dominant contract type)	Significant	Significant	Significant	Significant	Significant
Success of projects	0.004 (0.01)	0.009 (0.02)	0.004 (0.01)	0.005 (0.01)	0.009 (0.02)
Size of customer projects	-0.0001 ** (0.00009)	-0.0001 ** (0.00009)	-0.0001 ** (0.00009)	-0.0001 * (0.0001)	-0.0001 * (0.0001)
Likelihood ratio test	2270 on 23 df ***	2348 on 24 df ***	2273 on 24 df ***	2308 on 24 df ***	2378 on 26 df ***
Nagelkerke R2	11.90 %	12.31%	11.92%	12.10%	12.47%
Delta Nagelkerke R2		0.41%	0.02%	0.20%	0.57%
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level Standard error in parentheses					

Table 52: Proportional Hazard Models – Coefficients

The survival models for the different strengths of turnover influence are shown in Table 52. A base model, which only contains the control variables, was also developed.

The survival model for the turnover influence from current, direct relationships (Model 1 in Table 52) shows a highly significant influence of 3.16. Therefore, hypothesis *H1: Turnover in* *the current, direct organizational network of an IT professional increases the probability of turnover* is supported.

The survival model for the turnover influence from former, direct relationships (Model 2 in Table 52) shows a significant influence of 1.95. Therefore, hypothesis *H2: Turnover in the former, direct organizational network of an IT professional increases the probability of turnover* is supported.

The survival model for the turnover influence from current, indirect relationships (Model 3 in Table 52) shows a highly significant influence of 0.52. Therefore, hypothesis *H3: Turnover in the current, indirect organizational network of an IT professional increases the probability of turnover* is supported.

In addition to Models 1 to 3 that analyze the influence of the three strengths of turnover influence individually, we constructed a fourth model that analyzes all three strengths together. The survival model shows that strength of turnover influence from current, direct relationships (2.95), strength of turnover influence from former, direct relationships (1.57) as well as strength of turnover influence from current, indirect relationships (0.44) have a positive significant influence. This shows that the conclusions drawn previously are still valid.

Besides the likelihood ratio tests, we reported Nagelkerke's pseudo-R-squared (Nagelkerke, 1991). The base model has an explanatory power of 11.90%. Model 1 and Model 3 increase this explanatory substantially by 0.41% and 0.20%, respectively. Model 2 shows smaller improvement of 0.02%. In general, the pseudo-R-squares of our models are similar to the values of other turnover research studies using survival models such as those reported by Mossholder et al. (2005).

1.2.5 Discussion

We find that the turnover of an IT professional increases the probability of further turnover within the organizational network. Not only are the current, direct co-workers influenced, but there are also effects of the turnover on indirect and former co-workers. Contagious effects of individual turnover cases can lead to collective turnover that is unevenly distributed over time.

1.2.5.1 Limitations

This research is subject to limitations. First, we used a data set from a single IT company, which might weaken the generalizability of the obtained results. However, interviews with IT professionals from different companies support our claim that turnover in the organizational network of IT professionals increases the probability of further turnover.

Second, we do not analyze our proposed IT turnover contagion theory as a process theory on the individual level (Bartunek et al., 2008) but rather analyzed the spread of turnover in the organizational network as a variance theory. Using a qualitative approach to study the consequences of an individual's turnover on directly or indirectly connected team members could inform our understanding of collective turnover and provide additional factors to enhance our theory development.

Third, there are limitations related to the construction of the organizational network. We considered only second neighbors in the current, indirect network. However, due to the high connectedness of the network, the number of second neighbors is already very high. On average, the number of second neighbors influenced by a turnover case is 436. Additionally, we analyzed only the circumstance in which there had been a turnover in the indirect network and not the intensity of the influence. Higher order neighbors as well as the intensity of turnover influence in the indirect network could be analyzed by a diffusion process algorithm that simulates the distribution of the turnover intensity in the organizational network. Dasgupta et al. (2008) used a similar approach for predicting the churn of mobile phone customers based on their social network, which was based on the call history. In addition, we constructed the organizational network based on the amount of time worked together on the same project. We cannot, however, control for other ways in which relationships might have developed such as having participated in the same training or workshop or being part of the same company sport group.

1.2.5.2 Theoretical Implications

An IT Turnover Contagion Theory

We contribute to IT turnover research by showing that turnover spreads within organizational networks of IT organizations. We have developed an IT turnover contagion theory that integrates the unfolding model of voluntary turnover with a network perspective. Our developed theory is in line with the context-specific theorizing described by Hong et al. (2014). We have contextualized and transferred the findings of Felps et al. (2009), Krackhardt and Porter (1986) and Feeley and Barnett (1997) to the IT domain.

The developed IT turnover contagion theory consists of two parts. First, information about the turnover is shared in the organizational network by the remaining co-workers. This contagion process makes it possible that also IT professionals with no direct connection with the turnover case are affected. The second part of the theory considers the influence on the individual IT professionals. Receiving information about the turnover of a co-worker is perceived as a shock (Nyberg & Ployhart, 2013).

In IT, the organizational network is less stable and more widespread with many indirect connections compared to other industries (Felps et al., 2009). This is due to the nature of IT work. IT workers develop strong relationships with co-workers, as most of the work is conducted in teams with high levels of collaboration (Madsen & Matook, 2010; Tang & Kishore, 2010; Vidgen & Wang, 2009). In addition to professional relationships, IT team members develop strong personal relationships, which continue even after the work relationship has ended (Kram & Isabella, 1985; Markus & Kitayama, 1991; Sluss & Ashforth, 2007). IT projects are often conducted in fluid teams, this means IT professionals collaborate with professionals with expertise in other areas (Huckman & Staats, 2011; Huckman et al., 2009). Thus, their network is widespread within the organization.

Our data suggests that turnover spreads widely through this organizational network. First, we find that turnover spreads among the current direct co-workers. As they have a close relationship with the IT professional committing turnover and get first-hand information about the extenuating circumstances, the turnover represents a shock event after the unfolding model. However, in addition to reasoning based on the IT turnover contagion theory, other mechanisms, such as stress due to an increased workload (Ahuja et al., 2007) and alienation caused by the departing IT professional (Sluss & Ashforth, 2007), are also likely to be responsible for further turnover among the current direct co-workers. The spread of information within the current, direct organizational network is mostly driven by direct professional relationships between the departing IT professional and the remaining co-workers.

Second, our results suggest that turnover also spreads among past direct contacts. Some of an IT professional's former work relationships are likely to have turned into friendships (Kram & Isabella, 1985). It is highly possible that the IT professional committing turnover actively shares information on plans to leave the company with friends. This shock event triggers further turnover among friends. Similar to the situation of current co-workers, an IT professional committing turnover may try to convince friends to join him/her at the new employer (Sluss & Ashforth, 2007). The spread within the past, direct organizational network is primarily driven by direct personal relationships. However, as these relationships do not develop for every former professional relationship, we find lower effect levels in the data.

Finally, our data suggests that turnover spreads in the indirect network as well. Turnover events can influence other IT professionals of the same organization that do not have a direct relationship with the person who is leaving. As turnover is a notable event, it is likely that it causes workplace gossip (Foster, 2004; Grosser et al., 2010; Kurland & Pelled, 2000). Thus, information about the turnover spreads through the organizational network and triggers further turnover. This shows that the turnover of an IT professional does not only affect isolated groups of IT professionals, but the whole organization.

Our work contributes not only to IT turnover research, but also to turnover research in general management literature. Research on the spread of turnover in the organizational network has thus far only examined the spread of turnover in small and limited work groups (Feeley & Barnett, 1997; Felps et al., 2009; Krackhardt & Porter, 1986). These studies did not consider the spread of turnover among former work relationships and among indirect contacts.

We do not claim that turnover contagion effects are the main factors leading to the turnover of an IT professional. Turnover intention can be seen as a continuum that varies over time (Josefek & Kauffman, 2003). If a certain threshold is surpassed, the respective IT professional actually commits turnover (Josefek & Kauffman, 2003). The value of the turnover intention is influenced by various different factors (Joseph et al., 2007). Receiving information about the turnover of another co-worker adds to the turnover intention. However, it could also trigger a re-evaluation of the current situation. It is unlikely that a continuous evaluation of whether or not the threshold has been surpassed has been conducted. Receiving information about the turnover of a co-worker is a shock event that starts a thinking and re-evaluation process. To sum up, our proposed theory on turnover contagion provides a supplementary perspective to existing theories of turnover. We maintain that it is unlikely that the contagion based shock event alone is the main factor precipitating turnover of an IT professional; rather, a combination of events and situations actually trigger turnover.

Collective Turnover

Our study advances research on collective IT turnover. Turnover research in management literature has moved its focus to collective turnover in recent years (Hausknecht, 2017; Hom et al., 2017), but IT turnover research remains vastly silent on this topic (Moore & Burke, 2002; Naidoo, 2016). To date, the focus of IT turnover research has generally focused on individual level turnover and has treated turnover cases within IT organizations as independent (Dinger et al., 2015; Joseph et al., 2007; Thatcher et al., 2002). Our results, however, suggest that the turnover cases within IT organizations might be related to one another, a finding similarly reported by other researchers (Naidoo, 2016).

Existing quantitative studies on collective turnover do not consider the distribution of collective turnover cases over time (Ang & Slaughter, 2004; Ferratt et al., 2005). They implicitly assume an even distribution over time. The qualitative study on collective turnover of Naidoo (2016), for example, hints at an uneven distribution of collective turnover, but does not explicitly consider it. The ability of companies to cope with collective turnover is dependent on the distribution of the collective turnover cases (Nyberg & Ployhart, 2013), a situation especially applicable for IT organizations. Finding replacements in a short time frame and keeping projects running is very difficult for IT organizations due to the shortage of qualified professionals on the job market (Streim & Pfisterer, 2014; Thibodeau, 2012). Although an IT organization might be able to find a few replacements for the IT professionals that have left, these employees may require specialized training to acquire the necessary skills and knowledge to productively participate in the project (Reich, 2007). This paper shows how an uneven distribution of collective turnover develops through contagion effects within the organizational network. Based on this knowledge, it is possible to develop strategies against contagion effects of collective turnover.

Turnover Culture

We advance and empirically validate theoretical work on turnover culture (Burke & Moore, 2004; Moore & Burke, 2002). Intensity and direction have been identified as important determinants of turnover culture (Cooke & Rousseau, 1988; Moore & Burke, 2002). We contribute to the intensity dimension by showing that relationships with co-workers outside of the current work group are important for the development of turnover culture. The high turnover culture existing within a specific workgroup can foster high turnover culture throughout the entire organization.

We contribute to the direction dimension by incorporating the unfolding model of voluntary turnover with turnover culture. We show that a shock event that affects several members of a workgroup, like the turnover of another team member, can contribute to a high turnover culture.

1.2.5.3 Practical Implications

Our results also have implications for practice. First, IT managers might not see the turnover of one professional as problematic, but our results show that the probability of further professional turnover increases as a result. Previous research has shown the negative influence of collective turnover on performance (Hancock et al., 2013; Hancock et al., 2017; Hausknecht & Trevor, 2011; Heavey et al., 2013). Therefore, managers should take each turnover event seriously and consider retention measures for the remaining co-workers. Information about the turnover of a co-worker might not be the main factor that triggers turnover; IT managers should consider factors such as workload, stress level or job characteristics, to lower the turnover intention of the remaining IT professionals.

Second, as our results show that one turnover case leads to more turnover in the organizational network, IT managers should consider when and where to assign new employees and to possibly avoid placing them in the organizational network of an IT professional with a high turnover intention.

Third, our results suggest that IT professionals in the indirect network are also influenced by turnover, which is due to the spread of gossip within the organization. As gossip contains a subjective evaluative perspective (Kurland & Pelled, 2000) on the turnover event, IT managers should create transparency to prevent false interpretations.

Burke and Moore (2004) suggest using a monetary reward to discourage high turnover culture. In this approach, a monetary incentive is offered to a workgroup if the turnover rate within this workgroup is below a designated value. This influences group internal processes and marks turnover undesirable behavior by the clan (Chua et al., 2012). This “reward” could, however, create a tense and unpleasant atmosphere in a workgroup.

1.2.5.4 Future Research

Based on our analysis, we call for more research on collective turnover (Hausknecht, 2017; Hom et al., 2017; Naidoo, 2016). The number of studies on collective turnover in the IT domain is still limited despite its negative influence on company performance (Hancock et al., 2017; Hausknecht & Trevor, 2011). Future research could analyze the indirect network in more detail. For example, how far does turnover spread within the current, indirect network? As the amount of information is likely to decrease as information is passed from professional to professional, the influence of this information should decrease based on the number of ties between these professionals. Methodically, this could be done with a diffusion process-based approach (Dasgupta et al., 2008).

Another possible area for future research is to analyze the influence of contextual factors of the IT professionals on the spread of turnover. First, the influence of the hierarchical position of the professional that has committed turnover could be analyzed. Studies have found that hierarchy plays a significant role for several turnover antecedents and turnover intention (Ballinger, Cross, & Holtom, 2016; Ballinger et al., 2010; Cole & Bruch, 2006). Because they have access to more information (Salancik, 1995), the turnover of a professional at higher hierarchical levels could have a great influence on colleagues . However, due to the high frequency of the use of agile project management methods that deemphasize the importance of hierarchy, the effect of hierarchy should be smaller in the IT domain than in other business sectors. Krackhardt and Porter (1986) have shown that professionals have a higher probability of turnover if someone in their social network with a high perceived similarity has left the organization. Future research could analyze if the similar-to-me effect (Rand & Wexley, 1975) influences the strength of turnover.

The satisfaction of the professional committing turnover should be further analyzed. If the satisfaction is low, it is likely that mostly negative information about the reason for turnover is spread among co-workers. Work or job satisfaction could also be influential in interpreting the turnover of a co-worker. More than likely, information on negative or low rather than positive or high job satisfaction is circulated through the organizational network. Other possible contextual factors of the professionals could be for instance gender, age or educational background.

1.2.6 Appendix

1.2.6.1 Appendix A – Robustness Check

Variables	**Base model**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Strength of turnover influence from current, direct relationships		3.17 *** (0.28)			2.98 *** (0.28)
Strength of turnover influence from former, direct relationships			1.62 ** (1.32)		1.98 (1.48)
Strength of turnover influence from current, indirect relationships				0.43 *** (0.08)	0.34 *** (0.08)
Job Embeddedness	-0.001 * (0.0006)	-0.001 (0.0006)	-0.001 * (0.0006)	-0.002 *** (0.0007)	-0.002 *** (0.0007)
Factor(gender)	Insignificant	Insignificant	Insignificant	Insignificant	Insignificant
Factor(age)	Significant	Significant	Significant	Significant	Significant
Business confidence	-0.006 * (0.003)	-0.005 (0.003)	-0.006 (0.003)	-0.005 (0.003)	-0.005 (0.003)
Unemployment rate	-0.43 *** (0.05)	-0.42 *** (0.05)	-0.43 *** (0.05)	-0.42 *** (0.05)	-0.41 *** (0.05)
Factor(dominant industry)	Significant	Significant	Significant	Significant	Significant
Factor(dominant contract type)	Significant	Significant	Significant	Significant	Significant
Success of projects	0.004 (0.01)	0.009 (0.02)	0.004 (0.01)	0.006 (0.019)	0.009 (0.02)
Size of customer projects	-0.0001 ** (0.0000)	-0.0001 ** (0.0000)	-0.0001 ** (0.0001)	-0.0001 ** (0.0001)	-0.0001 ** (0.0001)
Likelihood ratio test	2270 on 23 df ***	2348 on 24 df ***	2272 on 24 df ***	2298 on 24 df ***	2369 on 26 df ***
Nagelkerke R2	11.90 %	12.31%	11.91%	12.05%	12.41%
Delta Nagelkerke R2		0.41%	0.01%	0.15%	0.51%
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level Standard error in parentheses.					

Table 53: Proportional Hazard Models – Coefficients – 26 Weeks

Variables	Base model	Model 1	Model 2	Model 3	Model 4
Strength of turnover influence from current, direct relationships		3.40 *** (0.29)			3.23 *** (0.30)
Strength of turnover influence from former, direct relationships			1.70 (1.29)		1.22 (1.41)
Strength of turnover influence from current, indirect relationships				0.52 *** (0.09)	0.46 *** (0.09)
Job Embeddedness	-0.001 * (0.0006)	-0.0009 (0.0006)	-0.001 * (0.0006)	-0.002 *** (0.0007)	-0.002 *** (0.0007)
Factor(gender)	Insignificant	Insignificant	Insignificant	Insignificant	Insignificant
Factor(age)	Significant	Significant	Significant	Significant	Significant
Business confidence	-0.006 * (0.003)	-0.005 (0.003)	-0.006 * (0.003)	-0.005 (0.003)	-0.005 (0.003)
Unemployment rate	-0.43 *** (0.05)	-0.42 *** (0.05)	-0.43 *** (0.05)	-0.42 *** (0.05)	-0.42 *** (0.05)
Factor(dominant industry)	Significant	Significant	Significant	Significant	Significant
Factor(dominant contract type)	Significant	Significant	Significant	Significant	Significant
Success of projects	0.004 (0.01)	0.008 (0.02)	0.004 (0.01)	0.005 (0.01)	0.009 (0.02)
Size of customer projects	-0.0001 ** (0.0000)	-0.0001 ** (0.0000)	-0.0001 ** (0.0001)	-0.0001 ** (0.0001)	-0.0001 ** (0.0001)
Likelihood ratio test	2270 on 23 df ***	2347 on 24 df ***	2271 on 24 df ***	2308 on 24 df ***	2377 on 26 df ***
Nagelkerke R2	11.90 %	12.31%	11.91 %	12.10 %	12.46 %
Delta Nagelkerke R2		0.41%	0.01 %	0.20 %	0.56 %
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level Standard error in parentheses.					

Table 54: Proportional Hazard Models – Coefficients – 78 Weeks

This robustness check considers the separation between the current and the past organizational network. In the main analysis, if two employees had not worked together in the previous year, they were considered in the past organizational network. In this robustness check, we analyze whether the results differ when considering 26 weeks (0.5 year) and 78 weeks (1.5 years) for the separation between the current and the past organizational network.

Table 53 shows the results of the survival analysis for half a year. These results do not differ from the exception that strength of turnover influence from former, direct relationships is slightly insignificant in Model 4. However, as strength of turnover influence is significant in Model 2, our conclusion remains unchanged.

Table 54 shows the results of the survival analysis for 78 weeks. The results for 78 weeks do not differ from 26 weeks and 52 weeks with the exception that past relationships do not show significant influences. However, this might be related to the fact that the unit of measure, 78 weeks, is too long. It is likely that possible friends have moved to another department where they do not regularly encounter the former co-worker or they have already left the organization.

2. Summary of Results

This section summarizes the key results of the publications of this dissertation.

Publication	Key Results

P1	• The formation of subgroups differs between projects with an agile project management method and a traditional project management method
	  o Task assignment is the dominant factor that leads to the formation of subgroups in traditional projects
	  o Previous ties between team members is the dominant factor that leads to the formation of subgroups in agile projects.
	• Location and language lead to the formation of subgroups in both methods.

P2	• Subgroups based on team familiarity have a positive influence. • The negative relationship between subgroups based on task familiarity and project performance cannot be fully supported.
P3	• Subgroups based on having experienced a project failure have a positive influence on project performance.
P4	• Theoretical model that project failure influences the turnover of IT professionals

P5	• Turnover spreads within IT organizations.
	  o It spreads among current team members.
	  o It spreads among former team members
	  o It spreads among indirect contacts within the organization

P6	• IT professionals that commit turnover differ regarding e.g. their career goals, their relationships within the organization and their current attitude to the job • Retention actions have to be specifically tailored to the individual IT professional
P7	• Environmental uncertainty and transaction frequency are the only TCE constructs that have a high explanatory power • Behavioral uncertainty and asset specificity are only of minor relevance.
P8	• Environmental uncertainty is the only TCE construct that has a strong effect on the contract form • The other three TCE constructs have weak or trivial effects. • Client and industry constructs have strong effects on contract form.
P9	• The danger of opportunistic behavior within the ITO market has decreased over the past few years. • The ITO market has increased its maturity and can be separated into an immature phase, occurring between 1997 and 2001, a transition phase, occurring between 2002 and 2008 and a third phase which occurred after 2008.

Table 55. Overview on Key Results

2.1 Results: Subgroups

The first research question "How do subgroups form and what is their influence on the performance of ITO projects?" was addressed by publications P1, P2 and P3.

Regarding the formation of subgroups in ITO projects, publication P1 has found that the formation of subgroups is dependent on the project management method. It has revealed that task assignment is the dominant factor that leads to the formation of subgroups in traditional projects, whereas previous ties between team members is the dominant factor in agile projects. Additionally, publication P1 revealed that location and language lead to the formation of subgroups in both project management methods.

Regarding the influence of subgroups, publications P2 and P3 have revealed that subgroups influence the performance of IT projects. Publication P2 found that subgroups based on team familiarity have a positive influence. However, the negative influence on project performance of subgroups based on task familiarity could not be fully supported. Publication P3 showed that subgroups based on team members that have experienced a project failure is positive for project performance.

2.2 Results: Turnover

The second research question "Is turnover influenced by external events and retention strategies?" was addressed by publications P4, P5 and P6.

Regarding the influence of external events, or shock events in the sense of the unfolding model of voluntary turnover theory, are considered by publications P4 and P5. P4 develops a theoretical model on the relationship between project failure that are very common in the IT domain and turnover of IT professionals. As project failures evoke strong negative emotions, such as frustration, disappointment, depression, anger or doubts about one's work (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011), they should be a shock event and increase the probability of turnover. Publication P5 finds that the turnover of a co-worker seems to be a shock event and, due to this, turnover spreads within the organization. The turnover of an IT employee increases the probability of turnover (1) among current team members, (2) among former team members, as well as (3) among indirect contacts within the organization.

Publication P6 considers retention strategies for IT professionals. It shows that IT professionals that commit turnover differ regarding e.g. their career goals, their relationships within the organization and their current attitude to the job. Seven different types of IT professionals that commit turnover are found. Additionally, publication P6 reveals that retention actions have the highest probability for a successful retention if they are tailored to the previously identified types of IT Professionals.

2.3 Results: ITO Governance

The third research question "Which constructs should be part of a new analytical framework of IT outsourcing?" is considered by publications P7, P8 and P9.

Publication P7 finds that environmental uncertainty and transaction frequency are the only TCE constructs that have a high explanatory power for analyzing the choice of governance for ITO projects. Behavioral uncertainty and asset specificity are only of minor relevance. Publication P8 is based on Publication P7, but comes to the conclusion that only environmental uncertainty is a TCE construct with a strong effect on the contract form. The other three considered TCE construct, behavioral uncertainty, asset specificity and transaction frequency have weak or trivial effects. Publication P8 additionally evaluates the influence of constructs on the client and industry level. It is shown that the history of contracting between the vendor and the client as well as the industry of the client have a significant influence on the contract type.

Publication P9 finds that the danger of opportunistic behavior, which is a central assumption of TCE theory, has decreased on the ITO market over the past few years. This has been analyzed based on the maturity of the ITO market. The results show that the ITO market has increased its maturity and can be separated into an immature phase, occurring between 1997 and 2001, a transition phase, occurring between 2002 and 2008 and a third phase which occurred after 2008.

3. Limitations

All research is subject to limitations. The detailed limitations of each publication can be found in Part B in each publication. This chapter discusses general limitations of this cumulative dissertation. Some of them are related to shortcomings of the employed data set. Despite these shortcomings, the data set offers several unique possibilities for research. For instance, it contains detailed and reliable data on each project conducted by the ITO vendor that provided the data set during the covered time period. Additionally, it contains the complete work history of all employees of ALPHA.

3.1 Single Data Set

The data set that has been employed by most papers of this cumulative dissertation is limited by the fact that it comes from a single company. This might limit the generalizability of the obtained results. It could be the case that there are company specific effects that have influenced the obtained results.

However, ALPHA was founded nearly two decades prior to the start of the data set and was one of the largest companies of its sector during the entire time covered by the data set. ALPHA is quite diversified and offers a broad range of different ITO activities. Due to this, the data set should be typically for the ITO industry.

Unfortunately, obtaining a second data set that is comparable to the existing one is quite difficult as an extensive amount of trust is necessary between the organization and the researchers. The data set contains several confidential aspects of the organization, like the profitability for certain industries or customers.

3.2 Data Quality

In general, the data quality of the data set is very good. However, there are certain aspects that are worth mentioning. For instance, the data set comes from different IT systems that have not been designed to be integrated. Due to this, different primary keys exist for the same employee, which made the integration of data challenging.

The IT systems have also been introduced at different points in time. The IT project controlling system has been introduced in 1995 and was in use by all parts of ALPHA after 1996. The first human resource management systems have been introduced in 2008 and all of them have been in use since 2009. Therefore, it is not possible to use the whole data set for every research question.

As the data comes from systems that have been used in practice, a few data fields are of low quality. For instance, the field expected revenue in the project management system has often been filled out with 0€ or 1€. It used to be a mandatory field, but estimating the revenue was sometimes very effortful for the project manager. However, as the project management system has also been used for billing the customers, most of the data is very reliable.

It has to be noted that the turnover survey was sent out to all IT professionals that committed turnover between January 2008 and May 2013. However, the response rate was about 15%. Therefore, the response could be biased. For instance, the size of the turnover types found in publication P6 should not be analyzed. Never the less over 300 responses should be large enough that all turnover types are present.

3.3 Operationalization of Constructs

The operationalization of some theoretical constructs was challenging. When employing surveys, quite often an established sets of questions for operationalizing a certain construct exist. However, this is not the case for the analysis of archive data sets.

It was not always possible to capture the full richness of a constructs as specified by the original theory. It was necessary to operationalize a construct with the data provided by the employed data set. Collecting additional data was not possible due to large number of projects and employee and due to the fact that the projects have already been finished. This was especially an issue in publications P7 and P8, as we tried to evaluate the explanatory power of TCE constructs. In order to address this limitation, we tried to operationalize the constructs similar to previous studies.

During the operationalization of some constructs, it was necessary to use certain cut-off values. For instance, in publication P9, it was assumed that the first 5 projects are considered a new relationship, in publication P5 it was assumed that contagious effects spread among contacts of the last year, or in publication P3 it was assumed that a project is a failure, if it has generated a loss of at least 10.000€ and a profitability of less than -20%. There is no source or clear reasoning for generating the right cut-off values. We based them mainly on discussions with IT experts. In order to address this limitation, we conducted several robustness checks, where the cut-off value has been varied.

3.4 Moderate Explanatory Power of Models:

Some of the statistical models that estimate project performance or turnover only show a moderate explanatory power. Project performance is a very complex construct that cannot be easily estimated with a few variables. However, the obtained values for adjusted R-squared are similar to other studies that employed large project archive data sets and analyzed project performance (Hoermann et al., 2015; Huckman et al., 2009).

Turnover is as well a very complex construct that is influenced by work-related factors, but also by private factors. Our approach made it only possible to evaluate the influence of work-related factors. As factors influence turnover that are not considered by the theory that is tested, a moderate explanatory power is common in turnover research (Hom et al., 2017).

3.5 No Data on Psychological Mechanisms

As the employed data set comes from the IT systems of an organization, it does not contain psychological data of the employees. Due to this, it is not possible to analyze the underlying psychological mechanisms that lead to turnover or to the formation of subgroups. For instance, the unfolding model of voluntary turnover is formulated as a process theory (Bartunek et al., 2008). Due to the lack of data, it is only possible to analyze the relationship between shock events and turnover as a variance theory. Similarly, it is not possible to analyze the existence of subgroups in project teams, but only to analyze situations where the emergence of subgroups is likely. This limitation of the data set can be address with a mixed-methods approach where a qualitative study focuses on the underlying psychological mechanisms.

4. Contributions

This dissertation contributes to theory and practice in several ways. In general, it contributes to the limit empirical research on ITO vendors, which has been pointed out by Lacity et al. (2010). ITO vendors face increased competition in recent years (Manning et al., 2011) and therefore have to understand how they can stay profitable and how the influencing factors behave. In the following, the contribution to subgroup research, IT turnover research and project governance research of this dissertation are outlined.

4.1 Contribution to Research on Subgroup

This dissertation contributes to the limited research on subgroups in two major ways. In the following, first, the contributions to research on the formation of subgroups and, second, the contributions to research on the influence of subgroups on the performance of IT projects are discussed. In general, our research shows the usefulness of subgroup theory in analyzing IT project teams.

First, this dissertation contributes to the limited research on faultlines and subgroups in the IT domain. Studies outside the IT domain have shown that identity-based factors like gender or age lead to the formation of subgroups (De Meulenaere et al., 2016; Yunhyung et al., 2015). Our results indicate that this is not the case in the IT domain. This could be due to the characteristics of the IT domain. Females are still underrepresented in IT teams and therefore there might not be enough representatives to form gender based subgroups. The age structure in the analyzed IT project teams was quite balance. This might have hindered the formation of age-based subgroups.

Second, this dissertation contributes to literature on virtual teams by supporting the claim that factors like language and geographical distance divide project teams (Gilson et al., 2015; Nader et al., 2009). Our results show that geographical distance as well as language leads to the formation of subgroups in agile as well as in traditional projects. Some of the studies on virtual teams are based on subgroup theory, but they did not consider IT project teams (Cramton & Hinds, 2004; O'Leary & Mortensen, 2010; Polzer et al., 2006). Additionally, these studies only consider geographical distance or cultural aspects as subgroup factors and disregard the broader picture. Our results show that there are also other factors that lead to the formation of subgroups.

Third, the obtained results on the formation of subgroups also contribute to literature on agile project management. Vidgen and Wang (2009) developed a framework that can be used to guide the organization of agile software development. However, they did not consider the possible formation of subgroups in their framework. Our results suggest, that subgroups are formed, if assumptions of agile methods are violated. A subgroup based on geographical distance forms if the assumption of a co-located team is not fulfilled. Additionally, a task-based subgroups emerges, if the team is divided based on the types of task, which should normally be not the case in agile methods.

Fourth, this dissertation contributes to research on the performance of IT projects by analyzing the influence of subgroups. Studies on the influence of subgroups on group performance have shown a positive as well as negative relationship in general management (Bezrukova et al., 2009; Carton & Cummings, 2013; Meyer et al., 2016; Sawyer et al., 2006). In line with the results in general management, we find that the influence of subgroups on project performance depend on the type of subgroup. Our results show that subgroups based on team familiarity and based on having experienced a project failure have a positive influence, whereas subgroups based on task familiarity tend to have a negative influence.

Fifth, the obtained results contribute to literature on the influence of task and team familiarity. Previous research has found that higher team as well as task familiarity have a positive influence on project performance (Banker & Slaughter, 1997; Espinosa et al., 2007; Huckman et al., 2009). We extend their finding by considering the distribution of these factors that likely lead to the formation of a subgroup if they are unevenly distributed. There is the call for taking a distribution perspective in addition to an average perspective when analyzing attributes at the team level that originate at the individual level in IT literature (Kudaravalli et al., 2017) as well as non-IT literature (Mell et al., 2014).

Sixth, this dissertation contributes to the limited literature on the effects of IT project failure. Studies suggest that IT organizations do not learn from failed projects (Ewusi-Mensah & Przasnyski, 1995; Kasi et al., 2008). However, our results suggest that whereas IT organizations might not learn from failed project, the involved IT professional seem to learn from the failed project and perform better in future projects. This is in line with research in other domains (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011).

In addition, the studies on subgroups within this dissertation contribute the practice. First, the factors that lead to the formation of subgroups within IT project teams are described. IT managers can address these factors in order to manage the emergence of subgroups.

Second, it is shown that the influence of subgroups depends on the type. Subgroups with a positive influence should not be addressed by IT managers, whereas subgroups with a negative influence should be resolved.

4.2 Contribution to Research on IT Turnover

This dissertation contributes to research on IT turnover in several ways, specifically to research on shock events and the retention of IT professionals.

First, it develops a theoretical model that describes the influence of project failure on the probability of turnover of the involved IT professionals. Previous research has shown that a project failure evokes negative emotions, such as frustration, disappointment, depression or anger among the involved IT professionals (Shepherd & Cardon, 2009; Shepherd et al., 2013; Shepherd et al., 2014; Shepherd et al., 2011). These emotions should be strong enough to be a shock event according to the unfolding model of voluntary turnover after Lee and Mitchell (1994).

Second, in addition to relating project failure to turnover, this dissertation contributes to research on shock events by analyzing the influence of turnover of a co-worker on the probability of turnover of an IT professional. Our results indicate that the turnover of a co-worker is a shock event and triggers further turnover. After the turnover of an IT professional, the probability of turnover increases among current team members, but also former team members and indirect contacts within the organization. This relationship suggests that turnover in the IT domain occurs in clusters and that a single turnover case can lead to collective turnover.

Third, this dissertation contributes to research on the retention of IT professionals (Agarwal et al., 2006; Agarwal & Ferratt, 1998; Bairi et al., 2011; Joseph et al., 2015; Thomas, 2015). Our results show that not all of the in literature described retention actions work for all IT professionals. The retention action should be aligned with the characteristics of the IT professional, like the current stage of his career, the motivations for working for the current employer, his relationships with co-workers or the current job situation.

In addition, this dissertation contributes to the practice. First, our results show that IT managers should take each turnover case serious as it could trigger further turnover within the IT organization. Previous research in general management has shown that collective turnover has a negative influence on performance (Hancock et al., 2013; Hancock et al., 2017; Hausknecht & Trevor, 2011; Heavey et al., 2013). IT manager should evaluate the turnover probability of the remaining IT professionals and take retention actions if necessary.

Second, especially publication 6 of this dissertation contributes to practice, because it addresses IT managers as an audience. It suggests specific retention strategies for seven different types of IT leavers, as the retention actions have to be aligned with the characteristics of the IT professional. These strategies are part of a larger retention process, which can be used by IT managers to choose retention actions for retaining an IT professionals that is considering leaving. In addition, publication 6 suggests six lessons that should be considered for retaining IT professionals: (1) Know Your Employees, (2) Optimize Career Opportunities and the Internal Job Market, (3) Align Retention Actions to the Organizational Context, (4) Keep the Door Open, (5) Conduct Post-entry Interviews, and (6) Financial Compensation Leads to Short-term Retention

4.3 Contribution to Research on Project Governance

This dissertation contributes to research on the choice of project governance and the applicability of TCE in ITO.

First, we contribute to the conversation critiquing the relevance of TCE for analyzing ITO (Lacity et al., 2011; Schermann et al., 2016). Lacity et al. (2016) and Karimi-Alaghehband et al. (2011) call for research that simultaneously evaluates the effects of the major TCE constructs, as IT studies typically employ only individual TCE constructs and not the whole theory. We consider all TCE constructs and found that environmental uncertainty is the only TCE construct that is relevant for the choice of governance. This supports the call of Lacity et al. (2011) and Schermann et al. (2016) to develop an own endogenous theory of ITO.

Second, this dissertation contributes to the development of an endogenous theory of ITO by suggesting that it should consider a multi-level approach. Such an approach has been advocated for a long time by e.g. Loh and Venkatraman (1992) or Lacity and Willcocks (1995). However it has not been considered so far. An exception is Aubert et al. (2012) that extended the TCE framework to include the industry levels of analysis. We show that factors on the task level, on the client level and on the industry level should be considered. At the task level, our results indicate that the choice of project governance is strongly influenced by environmental uncertainty. At the client level, the previous contract mostly determines the choice of project governance. At the industry level, the industry IT intensity has a high influence.

Third, this dissertation contributes to the limited research on the maturity of the ITO market (Bapna et al., 2013; Dongus et al., 2014; Tian & Qu, 2018). Our results show that it is possible to distinguish three different phases of ITO market maturity based on the danger of opportunistic behavior, which is a central assumption of TCE theory, as well as based on market concentration. The immature phase lasted until 2001, which corresponds to the year of separation between the immature and mature markets as defined by Susarla and Barua (2011) and Dongus et al. (2014). A transition phase occurred between 2002 and 2008. The results for the time after 2009 are not decisive. Klepper and Graddy (1990) have analyzed the lifecycle of several industries and found that the transition phase can last for several decades. Therefore, it is likely that the ITO market had been still in a transition phase after 2009. This would be in line with Bapna et al. (2013) that considered ITO market maturity as a continuous activity.

The obtained results also contribute to practice. They show that the design of an ITO contract should not be limited to a single transaction but also consider the history of contracting, and the client’s industry.

5. Future Research

This dissertation opens up several new avenues for future research. In the following, they are divided into three sections. First, future research on subgroups, IT turnover and project governance are discussed. Second, possibilities for future research based on the unique data set that is the basis of this dissertation are outlined. Third, possibilities for future research based on the Socio-Economic Panel are described.

5.1 Future Research based on this Dissertation

Detailed possibilities for future research can be found in each publication in Part B of this dissertation. In the following general possibilities for future research based on the three research questions of this dissertation will be discussed.

5.1.1 Future Research – Subgroups

Research question 1 considered the formation of subgroups in IT project teams and their influence on project performance. Regarding the formation of subgroups, several possibilities for future research exist.

First, publication P1 only considered the influence of one IT specific factor, namely the influence of the project management methodology. Future research could consider other IT specific factors, like expertise distribution or different hierarchical levels within the IT project team. In IT project teams, it is necessary that employees with diverse expertise collaborate for a successful IT project (Kudaravalli et al., 2017). It is likely that a knowledge-based subgroup emerges based on the distribution of expertise in the team (Carton & Cummings, 2012). Whether this is the case and which context factors have an influence could be addressed by future research. Agile practices have become very common in the IT domain. An important principle of agile methods is the self-management of the team (Moe et al., 2010). Due to this, the hierarchy is rather flat in IT organizations. Never the less, there are still different hierarchical levels, which can lead to the formation of resource-based subgroups (Carton & Cummings, 2012). Future research could consider the influence of different hierarchical levels in IT project teams on the formation of subgroups.

Second, future research could analyze how the formation of subgroups in IT differs from other domains. In publication P1, we showed that identity-based factors like gender and age do not lead to the formation of subgroups. This is opposed to previous findings in other domains, where identity-based subgroups were quite dominant (De Meulenaere et al., 2016; Yunhyung et al., 2015). In publication P1, we speculated about the reasons for this and attributed it to the nature of the IT domain, but future research could consider this phenomenon in more detail.

Third, another possible area for future research could be related to the question how subgroups can be resolved. In one of the IT teams considered in publication P1, we have found that they use team-building events to address possible subgroups and unite the team. In addition to such events, agile practices like pair programming or daily stand-ups could resolve subgroups or at least weaken possible negative influences of the subgroups.

Regarding the influence of subgroups, among others, there are the following possibilities for future research.

First, in this dissertation, only the influence of subgroups based on task familiarity, based on team familiarity and based on project failure experience on project performance has been analyzed in publication P2 and publication P3. Future research could consider the influence of other types of subgroups. Publication P1 has found that different locations leads to the formation of subgroups in IT project teams. Literature on the influence of virtual teams on project performance does not show a clear picture. De Guinea, Webster, and Staples (2012) conducted a meta-analysis and found that team virtualness has a negative influence on project performance. However, according to Maynard, Mathieu, Rapp, and Gilson (2012) and Kock and Lynn (2012) virtual teams can also have a positive influence. Future research could consider this in more detail and especially consider context factors like the task of the project. Another factor that has been found to lead to the formation of subgroups and could be addressed by future research is having different native speakers within the same team.

Second, publications P2 and P3 did not consider the task of the project. Kudaravalli et al. (2017) found that a centralization of team interaction is beneficial if the project has a technical focus, but harmful in projects with a design focus. Similarly, the influence of certain subgroups on project performance could be influenced by the task of the project. Future research could address this research gap.

5.1.2 Future Research – IT Turnover

Research question 2 considered the influence of shock events on the turnover of IT professionals as well as possible retention strategies to prevent turnover. There are several possibilities for future research.

First, publication P5 considered only one shock event, namely the turnover of another co-worker in the organizational network of an employee. Publication P4 theoretically considers the influence of project failure on turnover of IT professionals. However, the relationships has not yet been tested empirically with the data set of ALPHA. Future research could consider the influence of project failure in two ways. First, the influence of working currently on a failing project and, second, the influence of having worked on a failing project during the past few months.

Another possible shock events that could be considered by future research is the change of work environment. It changes quite drastically, if an employee works for a new customer or is assigned to a project with unknown other team members. Such changes could be large enough to be a shock event according to the unfolding model of voluntary turnover after Lee and Mitchell (1994). A new work environment can create stress, which has been found to be an antecedent of turnover (Moore, 2000), due to the new situations faced. However, a change of the work environment could also have positive influences and reduce the probability of turnover. It might reduce job boredom, which reduces job satisfaction (Kass, Vodanovich, & Callender, 2001).

Second, future research could focus on the job embeddedness theory after Mitchell et al. (2001). Due to its dynamic and complex character, the IT professionals face many shock events during their daily work. It is hardly possible to lower the number of shocks an IT professional has to face in order to reduce turnover rates. Another possibility is to increase his job embeddedness. There are a number of job embeddedness factors that could be addressed by future research. First, the links to other co-workers could be analyzed. These links could be separated in the number of links and in the intensity of the links. Due to fluid teams and the circumstance that IT professionals are part of multiple teams at the same time (Huckman & Staats, 2011; Niederman, 2016), IT professionals normally have many, but weak links. Second, the collaboration between the team members is more intense in agile projects, which should increase the job embeddedness of the team members (Brhel et al., 2015). Third, IT professionals are not only embedded within the organization, but also due to their private life in their community (Windeler, Moore, & Riemenschneider, 2015).

5.1.3 Future Research – Governance

Research question 3 considers factors that should be part of a new endogenous theory of ITO. Lacity et al. (2011) call for the development of such a theory. According to Whetten (1989), a theory consists of four parts:

1. *What*: This part considers the question, which factors should be part of the theory. The factors included in a theory should satisfy two criteria, comprehensiveness and parsimony. Comprehensiveness focuses on the question of whether all relevant factors are included in the theory. Parsimony calls for the exclusion of factors that add little additional value.
2. *How*: This part describes the causal relationship between the factors of the theory.
3. *Why*: This part considers the underlying logic of the theory. In comparison to the *What* and *How* part of a theory that focus on describing, this part focuses on explaining.
4. *Who, Where, When*: This part describes the boundaries of the theory and determines its generalizability.

Publications P7 and P8 mostly focused on the *What* and the *How* part of a theory. Based on our data set, we suggested a set of variables that should be part of this theory. We only considered the direct relationship of these variables on the choice of project governance. There are several possibilities for future research, which will be discussed in the following.

First, we do not claim that these are the only factors that should be considered, but these are the factors that could be considered based on the data set of ALPHA. Future research could analyze which additional factors should be part of the new theory. However, the two criteria, comprehensiveness and parsimony, which have been suggested by Whetten (1989), have to be considered.

Second, we have only considered the direct relationship of these variables on the choice of project governance, future research could also consider other relationships. For instance, it could be the case that the industry of the customer determines the environmental uncertainty of the project.

Third, we started to develop the underlying logic of the relationship between the proposed factors and the choice of project governance. Our thinking could be further developed and refined by future research

Fourth, our dataset contains project from only one firm and most of them have been conducted in Germany, Austria or Switzerland. This makes it difficult to test the boundaries of the theory with the dataset of ALPHA. Future research could analyze the proposed parts of a theory in different settings to evaluate the boundaries.

Publication P9 analyzed how one central assumption of TCE, the opportunistic behavior of the involved actors, has changed within the ITO market over time. It shows that the danger of opportunistic behavior has decreased over time. However, this study focused on the German ITO market. Future research could try to replicate the findings in other markets that might be less mature than the German ITO market.

5.2 Future Research based on the Employed Data Set

The employed data set offers many other possibilities for research than the areas addressed by this dissertation. In the following, exemplary possibilities for future research are described.

One possibility for future research is the analysis of the influence of training on turnover. The data set contains information like the duration, the date, the type of training, and whether it was conducted in-house or external on more than 18.600 trainings of employees of ALPHA. For instance, it is possible to deduct whether a training focused on general or firm specific skills based on the type of training. IT professionals constantly face the danger of professional obsolescence and might respond to this danger by committing turnover (Joseph & Ang, 2010; Zhang, Ryan, Prybutok, & Kappelman, 2012). Receiving training can address the danger of professional obsolescence. Additionally, training can increase the employees fit to the organization and therefore increase his job embeddedness. Surprisingly, previous research did not find a relationship between training and turnover (Joseph et al., 2015). This could be analyzed in more detailed with our data set.

Another area for future research is to consider the onboarding of new employees. This dissertation focused on the turnover of IT professionals and how it can be prevented as it creates high costs. Parts of these costs are related to recruiting of a new IT professional and the time till he is fully productive (Baroudi, 1985). The whole process can be divided into the following steps: Plan, Attract, Relate, Select, Win&Hire, and Onboarding (Laumer, Maier, & Eckhardt, 2014). A similar term for onboarding is organizational socialization, which describes how new employees acquire the attitudes, behaviors, and knowledge that are required to be fully productive in the new organization (Gruman & Saks, 2011; Van Maanen & Schein, 1977). There are only a few publications that consider the onboarding of IT professionals. For instance, Johnson and Senges (2010) analyze the onboarding process at Google as a role model for good onboarding. Major et al. (2007) describe the onboarding practices of high performing IT supervisors. The data set of ALPHA offers the possibility to analyze the onboarding of new employees regarding the trainings that they received and the projects they were assigned to. For instance, it could be analyzed whether the onboarding of employees differ according to their educational background.

The data set contains 13.402 yearly employee performance reviews that have been conducted between 2009 and 2015. In these reviews, the supervisor rates the respective employee based on his/her performance during the last year and future potential in the company. It could be analyzed whether the translation of potential into performance is trigger rather by receiving formal trainings or rather by gaining experience and knowledge through working on certain projects. Additionally, the employee as well as the supervisor answered a survey with more than 60 questions on topics like the motivation of the employee, the ability to work in teams or the willingness to travel or learn new topics. However, the data quality of the survey answers is limited. Never the less, this employee appraisal data offers due to its uniqueness and possibility to link it to the work history of each employee several possibilities for future research. For instance, employees with a substantial difference in the answers between the employee and the supervisor could be analyzed. It could be analyzed whether this deviation between self image and public image increases or decreases the probability of turnover.

Another possibility is the replication of studies on contract choice for IT outsourcing. For instance, Gopal et al. (2003) or Gefen et al. (2008), which employ archive data sets, could be tried to be replicated with the data set of ALPHA. Most of the variables used in these two studies can also be found in our data set. The AIS Transactions on Replication Research is a journal that exclusively publishes such studies.

5.3 Future Research based on the Socio-Economic Panel

The Socio-Economic Panel (SOEP), conducted by the “German Institute for Economic Research DIW” is a longitudinal study collecting information about people living in Germany. Since 1984, a total number of more than 86.000 people took part in the interviews, with up to 30.000 respondents annually. In total, there are 624.808 surveys recorded in the data set. The questions consider personal characteristics, the household, the occupation, the employment situation, the earnings, the health situation and satisfaction indicators (2018). The respondents stated their occupation based on occupational classification codes, which makes it possible to filter out employees that work in IT. In total, 942 of the interviewed people have experience in the field of IT. The Chair for Information Systems has access to the SOEP and could easily use it for future research.

A similar data set is the National Longitudinal Survey of the Youth (NLSY), which is available two versions (Bureau of Labor Statistics, 2019). Beginning in 1979 as well as in 1997, adolescents have been surveyed on a yearly basis. This data set has been used by Damien Joseph and colleagues for conducting studies on turnover and career paths of IT professionals (e.g. Joseph et al. (2015), Joseph, Boh, Ang, and Slaughter (2012) or Setor, Joseph, and Chan (2018)).

The SOEP has not yet been used for studies on turnover or career paths of IT professionals. As it is very similar to the NLSY, one possibility for future research would be conducting replication studies of the work of Damien Joseph and colleagues.

Another possibility for future research is the analysis of the current IT workforce in Germany. The high demand of IT professionals might have drawn professionals that do not have an IT education into IT. It could be analyzed whether this is the case and if yes, which factors have influenced this transition from the non-IT workforce to the IT workforce.

6. Conclusion

This cumulative dissertation analyzed the influence of human resource management and of project governance on the project success of IT outsourcing vendors. I considered the following research areas: (1) the formation of subgroups within IT project teams and their influence on project performance, (2) the influence of shock events on the turnover of IT professionals and possible retention strategies to prevent turnover, and (3) factors influencing the choice of project governance that should be part of an endogenous theory of IT outsourcing. These research areas have been analyzed with a mixed-method approach, but most studies have a quantitative approach due to access to a unique archive data set of a German IT outsourcing vendor. In total, this cumulative dissertation comprises seven publications that address these three areas. We find that (1.1) identity-based factors do not lead to the formation of subgroups, whereas geographical distance, language, previous ties and task assignment do, (1.2) depending on the type, subgroups have a positive as well as negative influence on project performance, (2.1) turnover spreads in the organizational network of IT organizations, (2.2) retention strategies have to be aligned with the characteristics of the respective IT professional, (3.1) environmental uncertainty is the only TCE construct with a high influence on the choice of project governance, and (3.2) an endogenous theory of ITO should consider a multi-level approach.

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Appendix A – Data set

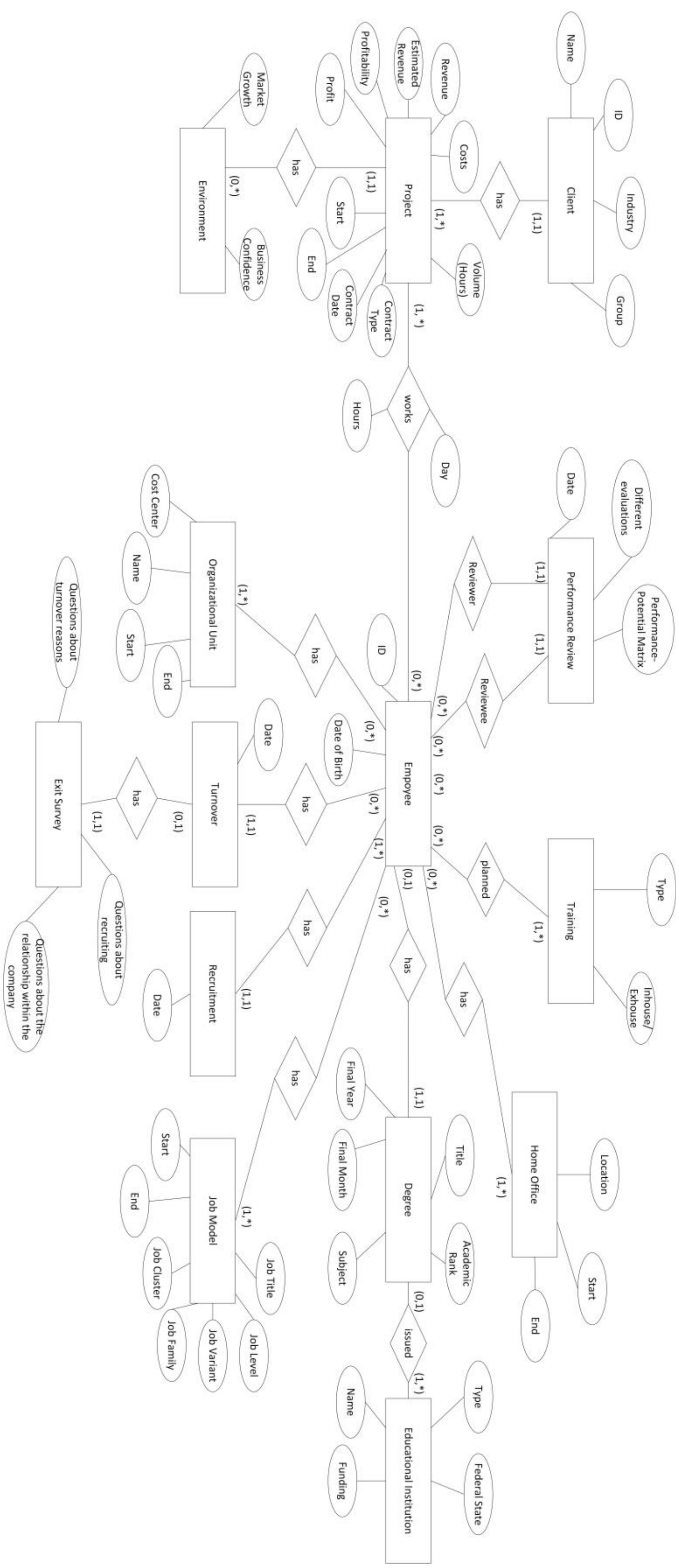

Figure 19: Entity Relationship Model of Data Set

Appendix B – Publication P1

Subgroups in Agile and Traditional IT Project Teams

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Abstract

This paper analyzes the formation of subgroups within project teams that apply agile methods and teams that apply traditional methods. Subgroups form based on faultlines, which are dividing lines regarding attributes of diversity of the team members. We conduct case studies of two agile projects and two projects with a traditional approach. We find that the formation of subgroups differs between the two methods. Task assignment is the dominant factor that leads to the formation of subgroups in traditional methods, whereas previous ties between team members is the dominant factor in agile projects. In addition, location and language lead to the formation of subgroups in both methods. Our analysis is exploratory and our data is limited to four teams. We contribute to the literature on team formation and groups in IT project teams and show that research should consider subgroups and potential consequences when examining agile and traditional software development methods.

1. Introduction

The success of IT projects depends, among other things, on the skills of the team members [1, 2]. However, the selection and combination of different team members is an ongoing challenge [1, 3]. Previous studies have found that heterogeneity among the team members increases creativity [4, 5]. At the same time, the heterogeneity of team members' attributes can also lead to the formation of subgroups within the project team [6, 7]. A subgroup is a subset of team members that is characterized by a unique form of a certain attribute (e.g. age, skill or status) [7].

Especially IT projects that apply agile methods, like Scrum or Extreme Programming demand team heterogeneity and foster close collaboration [8]. On the contrary, teams that follow traditional project management methods are selected based on their capabilities to conduct a pre-planned task [9]. Due to these differences in the way the team collaborates and the team conducts tasks, the formation of subgroups is supposed to differ between projects with agile methods and projects with traditional methods. Practitioners should consider the formation of subgroups when applying these project management methods, because they influence the performance of the project [10-13]. Additionally, if they are aware of the possible formation of subgroups, they can initiate actions that hinder the formation, like staffing and managing the project differently.

However, it remains unclear how subgroups form in IT projects with agile and traditional methods. Due to the differences in team composition and conducting tasks, different types of subgroups form in agile and traditional IT projects, based on faultlines, which are dividing lines that are based on attributes of diversity of team members [7, 14]. For instance, agile methods emphasize values like commitment, openness and respect [15]. This creates a different form of exchange between the team members [16], which in turn influences the formation of subgroups. As it remains unclear how subgroups form under agile methods and under traditional methods, it is difficult to develop actions that hinder the formation or weaken the influence of the subgroup. To address this gap, we seek to answer the following research question: *Which factors lead to the formation of subgroups in agile and traditional project management methods?*

We chose an exploratory case study design to answer this question. We analyze four IT development projects. Two projects have employed an agile method and two projects followed a traditional approach.

We find that there are differences in the formation of subgroups between agile methods and traditional methods. The primary factor that leads to the formation of subgroups in traditional projects is the task assignment. Agile teams are characterized by subgroups that are formed due to ties between team members that know each other from previous interactions. Additionally, we find that no matter if an agile method or a traditional method has been chosen, different locations and languages lead to the formation of very dominant subgroups.

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This paper is structured as followed. First, we present background information on faultlines and subgroups as well as on agile and traditional project management methods. This is followed by a presentation of the chosen research method. Then, we present the results and report on the found subgroups in agile methods and traditional methods. Finally, the theoretical and practical implications as well as limitations and possible future research are discussed. The paper ends with a short conclusion.

2. Theoretical Background

2.1 Faultlines and Subgroups

A subgroup is a subset of members of a work team, which is characterized by a unique interdependence that distinguishes the subset from other members of the team [7]. Subgroups are formed based on faultlines, hypothetical dividing lines, which split a team into multiple, homogeneous subgroups [14]. Faultlines are based on individual attributes, like education, gender or work experience. Team members, who share one or more of these characteristics, bond with each other and thus create a subgroup [17]. Previous literature has already identified possible faultlines (see table 1).

Table 1. Faultlines In Previous Literature

Faultline	Description
Demographic	Identity-based factors of team members like age, gender, race or religion [14]
Geographic	Factors related to the location or the distance between the team members [18]
Language/ Culture	Factors, like language, nationality or culture. Often related to geographic factors, but not necessarily the same [14, 19-21]
Personality	Factors that refer to the personality of the team members, like conscientiousness, emotional stability, attitudes, beliefs, values or cognitive style [22-24]
Employer related	Employer related factors, like tenure, function, pay, status or decision power [7, 14, 24, 25]
Knowledge	Factors like education or work experience, that related to the knowledge of the team members [7]

Within a team there might be several different faultlines, but not all of them are activated and lead to the formation of a subgroup [26].

Literature distinguishes three types of subgroups [7]. First, members of identity-based subgroups are characterized by the same characters or share similar values [27]. Second, knowledge-based subgroups are formed based on technical language [28]. Members of this type of subgroup often share information or use this form of exchange to solve problems and tasks together [7]. Third, resource-based subgroups are based on the idea of group conflict theory [29] as well as on theories of inequality and organizational ranks [30]. Members of this type of subgroup differentiate according to the ability to claim resources, such as decision power [7]. Therefore, resource-based subgroups often form based on the hierarchical level.

The effects of subgroups have been studied intensively, but the empirical results differ. While some studies suggest that subgroups also have positive effects for team members [10, 12], the majority highlights their negative consequences. In general, any type of faultline may have both, positive and negative impacts [13]. Positive effects of subgroups are mainly found related to knowledge-based subgroups [10, 12]. They have the advantage that they bring different forms of knowledge into one team [12].

Negative consequences are mostly related to identity-based and resource-based subgroups. Identity-based subgroups may lead to conflicts in the whole team, caused by ethnocentrism [31], especially when there are two strong subgroups of this kind in one team, which work against each other [12]. Resource-based subgroups in teams may lead to an asymmetry in perception of fairness and power centralization [7] which disturbs the common decision making process [32]. In general, subgroups may cause an interruption of the knowledge flow within the team, as subgroup members communicate primarily with other members of the same subgroups [11]. Another negative aspect is social loafing of individuals, which happens primarily in larger subgroups [33].

Especially difficult situations and crises foster subgroups and reinforce the barriers between individuals in the project team [34]. When these negative consequences occur in software project teams, it may have serious influence on the project success.

2.2 Agile and Traditional Project Management Methods

Agile methods gained popularity in recent years [8]. There are several different agile methods, like Scrum, Kanban and Extreme Programming, but Scrum is by far the most used one [35]. These approaches focus on the social nature of software development [16]. Values like commitment, openness and respect form the footing of all agile methods and lead to a higher perception of job satisfaction within software development teams [15]. Furthermore, additional factors like team awareness and team involvement foster cohesion within the team [16].

An important principle of agile methods is the self-management of the team [36]. Flat hierarchies and the possibility to decide how to accomplish work are fundamental aspects, which give the team higher responsibility in its work life and rises again the satisfaction level [37]. The basis for self-managing teams is a shared-decision making process, which demands respect and trust within the whole team [38].

Communication plays a special role within agile principles [39]. Agile methods trust in face-to-face communication, whenever it is possible [40] and see continuously exchange between team members, managers and customers as an important influence factor for project success. Frequent communication between team members supports not only performance and quality [41], but also promotes knowledge sharing in project teams [42].

Traditional methods are different from agile methods. They have a long tradition in IT development projects and are currently still broadly used, especially in the manufacturing industry [35, 43]. Traditional methods are characterized by a pre-planning stage that is followed by the execution, which makes them less flexible in comparison to agile methods [9, 43]. Additionally, unlike agile methods, they have a clear hierarchy within the team [9]. The collaboration is less close than in an agile project team. Daily meetings are not part of the methodology like in agile methods. As the task assignment is stable in traditional methods, the team members work together with the same few persons for most of the project time [9].

2.3 Subgroups within Agile and Traditional Projects

The previously described differences between agile methods and traditional methods should have different influences on the activation of faultlines and therefore on the formation of subgroups. Up to now, literature has only dealt with distributed agile teams and therefore has limited the perspective to geographical distance [44, 45]. First, the collaboration differs between projects with an agile and a traditional method [9]. The team members work much closer together under agile methods. Second, the fix task assignment in traditional methods leads more stable structured within the team [9]. Therefore, the same team members work always together whereas different ones work together in agile methods.

2.4 Distributed Teams as Example for Subgroups in Software Development

There is already extensive literature on virtual and distributed teams [46, 47]. However, this literature mostly lacks of consideration of subgroups, although geographical distribution is a factor that is likely to lead to the formation of subgroups [46]. The faultline factors in the case of virtual teams are location and language [18, 46]. Cramton and Hinds [31] theoretically expended the faultine model of Lau and Murnighan [14] to virtual teams, but did not empirically test their model. An exception is Polzer, Crisp [18] that analyse the activation of faultlines and subgroups in geographically dispersed teams. They found that subgroups form and that conflict is heightened and trust is decreased between the geographically dispersed subgroups. Another exception is O'Leary and Mortensen [48] that found that geographically based subgroups weaken team identification, lead to less effective transactive memory and increase team conflict.

As this brief overview of literature on virtual and distributed teams shows, most studies miss a consideration of subgroup theories. There are a few exceptions, but none of these studies have been conducted in the IT domain or consider also other types of subgroups, like identity-based or knowledge-based subgroups.

3. Research Method

To analyze factors that lead to the formation of subgroups, a qualitative design has been chosen. We decided to conduct a case study to answer our exploratory research question as it allows us to investigate phenomena in depth in its real-world context [49]. We explored the formation of subgroups in two agile IT projects and two traditional IT projects.

3.1 Case Selection

Table 2 shows the description of the selected cases. In general, we selected cases with a certain number of team member in order to increase the likeliness of finding subgroups [12].

Teams 1 and 2 are projects with an agile method and were conducted in a German IT company. Teams 3 and 4 are projects with a traditional method and were conducted in a German financial service company.

3.2 Data Collection and Analysis

Table 2 shows the number of interviews that were conducted in the four analyzed teams. In Team 1 nearly half of the team has been interviewed. More than half of the team members were interviewed in Teams 2 and 3. In Team 4 only about a quarter of the team members were interviewed. Although not all team members were interviewed, we still believe to have gotten thorough insights in all of the four teams.

We used grounded theory coding techniques to analyze the data and develop the faultline categories as introduced in the results section [50]. We based the coding categories on factors that could be possible faultlines within the project teams. The atlas.ti software package was used to support coding and analysis.

Table 2. Selected Cases and Interviews

Team	Project purpose	People	Locations	Project Management Method	Number of Interviews
1	Development of a software package concerning insurance	12	1	Scrum	5
2	Development of a business process management software	19	3	Scrum	12
3	Quality management of IT processes	15	2	Tradi-tional	8
4	Management of IT Change Requests	12	2	Tradi-tional	3

4. Results

4.1. Agile Method

The two agile teams were well-established, self-managing teams with motivated team members with a good reputation and company record of accomplishment in ISD projects. Both teams applied Scrum as agile method. We identified several faultlines and activated subgroups in each of the two teams. They are reported in table 3.

Our results suggest that demographic faultlines like age and gender are not activated. Team 1 and 2 only had two females respectively and therefore, the formation of a gender based subgroup is unlikely. An age based subgroup is not formed, because the team members in the two agile teams have a quite similar age between 20 and 40 years.

Knowledge and education related faultlines are not activated, because experts form groups only for the discussion of a certain topic and then dissolve again. Therefore, not stable subgroup is formed.

A faultline based on functions within the team has not been activated due to the generalist-approach of agile methods, where only the roles team member, scrum master and product owner exist. However, we found that in one team the product owner has been excluded from the retrospective because of his role. He perceived himself as ostracized.

Table 3. Theoretical and activated Faultlines

Faultline	Description	Activated	Rational for Activation
Age	Team members were in a similar age group.		Little variance
Gender	Only small share of team members was female		Not many females
Know-ledge / education	Experts assemble in groups, but only for the discussion of a topic and then separate again		Changing faultlines over time based on user stories are not stable
Function	Generalist-approach reduced number of roles, but product owner differed.		Product owner was the only one with a different role
Previous ties	Several team members had prior work (and educational) experience together.	X	The self-managed character makes it possible that the faultline is activated
Task / goal	Continuously changing tasks and therefore goals for each iteration.		Task-based subgroups are only temporary and not persistent
Geo-graphical distance	Developers work in two different offices in different countries.	X	Informal contacts are not possible
Language	Language in country A as project language, non-native speaking developers in country B.	X	Language barrier makes communication difficult

Due to the usage of user stories in agile methods that are carried out by different combinations of team members in each iteration, only temporal subgroups form for the time a user story is carried out. They then dissolve again right after finishing the user story.

In the following, we describe the most dominant subgroups that were formed due to activated faultlines.

In team 2, the most dominant subgroup was formed due to location- and language-based faultlines. Eight of the 19 team members were located on the company site in country A. The other 11 team members were located in a different company site in country B. The software developers in country B were not native speakers in the project's dominant language, but all team members in country A were. There was a variety in the language skills in the team in country B.

The subgroup manifests in the low number of interactions between the two team locations, but also in the perception of the team members, such as explained by one developer from country A:

"These people from the other location [country B] ... If there is not really anything, which has to be done together, we work rather isolated from each other. (System Architect 02_07)"

The formation of this subgroup is mostly due to the difficulties to communicate informally by mail, phone or video chat. This hinders closer ties between team members and reduces trust and a shared understanding. One team member mentioned that it would be positive to meet the team members from the other location to get to know them on an informal basis:

"Yes, it is positive for the project when we meet in person from time to time and to see the person and not just hear the voice, or read their mails. (System Architect 02_11)"

This communication barrier not only leads to the separation of the team, but also intensifies the relationships within the two parts of the team. In team 2, the projects dominant language is that of country A. The team members from country B often discuss the unclear issues first after the daily stand-up first internally and if this has not resolved the issue with a team member from country A:

"First of all, we try to clarify issues internally, and if there is any ambiguity, we'll get back to the [country A] team. (System Architect 02_11)"

This communication barrier not only exists due to different countries, but also because of separate offices in team 1. The office with the physical scrum board is the dominant office and most of the discussions take place in this office. Team members from other offices have to actively seek being part of the discussion and not being cut off from the information flow. One member of team 1 describes this as followed:

"If you have two separate offices, discussions stay within one office. First, you ask others from the same office and this discussion is not passed on to the other office room (Software Developer 01_02)"

In team 1, the most dominant subgroup was formed due to previous ties between some of the team members. Most of these team members knew each other from previous projects, but there was also the case where two team members happened to have gone to secondary school together. It was usual for these team members to have lunch together with team members from the previous project, where they also discussed issues concerning the current project. The scrum master described this subgroup as follows:

"Yes, [we are a subgroup], definitely, it's quite normal. If you've already spent two years together, there is of course a different kind of relationship. (Scrum Master 01_04)"

The formation of this subgroup is mostly driven by the close relationships between the team members that know each other. A subgroup based on previous ties between some team members can also be found in team 2, but it is only secondary due to the strong location based subgroup.

In team 2, we additionally find a strong task based subgroup. Normally, agile software development argues for a generalist approach, where every team member is theoretically responsible for every task. However, this team has been separated into technical consultants and into business consultants.

"You certainly have this [formation of a subgroup] between the technical consultants and the business consultants. (Scrum Master 02_09)"

4.2 Traditional Method

The two traditionally managed teams studied were well-established teams with motivated team members. We identified several faultlines and subgroups in each of the two teams. We report on them in table 4.

Similarly to the agile case, we find that demographic faultlines like age and gender are not activated in traditional method settings. Team 3 and 4 only had two females respectively and therefore, the formation of a gender based subgroup is unlikely. There is no strong age based faultline, because there was little variance in the age. Most of the people were between mid thirty and end forty, with one exception in team 3, where one member was 59 years old.

A knowledge based faultline is not activated, because people are assigned to a task based on their knowledge. Therefore, the dominant faultline is task.

A faultline based on function was not activated, although such a subgroup is likely in traditional methods due to the clear hierarchy. However, we did not find a strong hierarchical in the two analyzed teams and therefore no subgroups were formed.

We find that a faultline based on previous ties is not activated, because the team members are assigned to tasks and do not collaborate closely across tasks. Due to this, although there might be previous ties, they do not lead to the formation of a subgroup.

We find, that a task-based subgroup is the dominant subgroup, if traditional methods are used. Tasks in traditional methods are different from tasks in agile methods, because they take longer and, most of the time, people do the same task throughout the project. Therefore, the assignment to a task within a project with a traditional method separates the team and hinders close collaboration between the team members, which leads to the formation of subgroups. A member of team 3 describes this as follows:

"I mean, with people with whom you have relatively little to do, you have little exchange. With these, of course, you do not have this relationship on a personal level. (IT consultants 03_01)"

Table 4. Theoretical and activated Faultlines

Faultline	Description	Activated	Rational for Activation
Age	Team members were in a similar age group.		Little variance
Gender	Only small share of team members were female		Not many females
Know-ledge / education	Experts are assigned to tasks based on their knowledge		Task is the dominant factor that leads to the activation
Function	Clear hierarchies within teams		We did not find a hierarchical structure to be present in the teams
Previous ties	There are not many previous ties		People do not collaborate closely across tasks
Task / goal	Each team member has a fixed task that does not change	X	Task-based subgroups are formed
Geo-graphical distance	Developers work in different offices in different countries.	X	Informal contacts are not possible
Language	Language is set to be English, which is known by both parties	X	The mother tongue of a large portion of the team is German

Similarly to agile projects, we find that geographical distance and language are faultlines that are activated and lead to the formation of subgroups.

"Two members working on this task are in Germany and the other two in India. There are, therefore, two subgroups which result from the geographical separation of the team. (IT consultant 04_02)"

In team 3, we find that the team leader has decided that the team should have breakfast together every Monday. This team building effort has been introduced to implement a basis to exchange project related information across people that do not work on the same task.

4.3 Comparison of Subgroups In Agile And Traditional Methods

The results show that we find differences regarding subgroups between agile methods and traditional methods. Task-based subgroups are dominantly formed in projects with traditional methods. In agile projects, only temporary task-based subgroups are formed for the duration of specific user stories. This is due to the circumstance that tasks are different between the two methods. In traditional methods, tasks take longer and are over the entire term performed by the same persons. In agile methods however, tasks are shorter and performed by different combinations of people over time.

We find that previous ties leads to the formation of subgroups in agile methods, but not in traditional methods. In traditional methods, task-based subgroups are the dominant subgroup and separate the team into smaller parts that work on tasks. Previous ties are therefore only of minor relevance in traditional methods. Geographical distance as well as language are faultlines that are activated under traditional methods as well as under agile methods. Those are strong factors that divide the team members, because for instance it is hardly possible to build up an informal relationship with a person from another office location.

5. Discussion

5.1 Theoretical and Practical Contribution

Our results contribute to literature on agile and traditional methods. Vidgen and Wang [9] develop a framework that can be used to guide the organization of agile software development. However, their framework disregards the possible formation of subgroups. We extend the framework of Vidgen and Wang [9] by showing that subgroups play a role in agile software development. Our results show, that this is especially the case, when agile methods are violated. In one of the analyzed teams, the team was divided based on the kind of tasks that they had to perform. This has led to the formation of task-based subgroups. However, the division of the team based on types of tasks is not advised according to the principles of agile software development. Furthermore, geographical distance as well as language barriers lead to the formation of subgroups. As agile methods assume a co-located team, this violation leads to the formation of a subgroup. Therefore, Hossain, Babar [51] suggest that a scrum of scrum approach should be taken, if the team cannot be located in a single office space.

We also contribute to literature on agile and traditional methods by showing that the formation of subgroups differs between agile and traditional methods. In traditional methods, the dominant factor for the formation of subgroups is the task. Team members that have different tasks hardly interact with each other.

In general, it seems that there are less strong and severe subgroups in projects with agile methods than in projects with traditional methods. Additionally, our results suggest that IT managers use approaches, like the breakfast in team 3 to decrease the effects of the strong subgroups.

Second, we contribute to literature on virtual teams [46, 47]. We find that geographical distance as well as language leads to the formation of subgroups, no matter which type of development methodology is employed. This supports the claim of virtual teams literature that attributes like language and geographical distance can divide teams.

However, studies on virtual teams focus only on these attributes and mostly disregard subgroup theory [46]. For instance, Montoya-Weiss, Massey [52] analyzed conflict management in virtual teams, but did not consider literature on subgroups or faultlines, although they can be a source for conflicts within teams [7, 53]. Oshri, Van Fenema [54] analyze knowledge transfer within virtual teams, but do not consider that the flow of information is influenced by the subgroups within the team [55]. Theory on subgroups and faultlines could give these studies an alternative perspective.

This perspective has already been employed by studies on virtual teams in non IT settings [18, 48]. We extend this to the IT domain. Furthermore, only considering geographical distance or cultural aspects as factors disregards the broader picture. We find that previous ties in agile projects and the task assignment in projects with a traditional method do additionally have an influence.

Third, we contribute to the limited research on faultlines and subgroups in the IT domain. We show that identity-based factors like gender and age do not lead to the formation of subgroups. This is opposed to previous findings in other domains [56, 57]. We do not find support that identity-based factors like gender and age lead to the formation of subgroups. Our results suggest that this is caused by the nature of the IT section. As females are still underrepresented in IT-teams, there were not enough representatives to build this form of subgroups. Women are rather integrated in the whole team and get included in other subgroups that are independent from gender. Similarly, the age structure was balanced, which hindered the formation of age-based subgroups.

We contribute to practice by outlining which factors lead to the formation of subgroups in projects with agile methods and in projects with traditional methods. Subgroups within project teams are an issue in practice, because they influence the way how the team members interact and communicate with each other [11]. Due to this the performance of the project is also affected by the existence of subgroups within the team [10-13].

There are several ways how IT project managers can address the subgroups and faultlines in their teams. For instance, they can conduct team building efforts before the start of the project. Especially in the case of a project with several sites, it is advisable that the whole team has the possibility to informally exchange and get to know each other due to the strong subgroups based on geographical distance that we have identified.

5.2 Limitations

First, our results are limited by the circumstance, that we did not interview all members of the team. As subgroups might be perceptional [28], it is possible that we have missed certain subgroups. However, we interviewed quite a large share of the groups, which makes it unrealistic that we missed large or strong subgroups. Second, the analyzed teams differ in size and organizational context. Due to this, it is possible that we found subgroups that are not related to the project management method, but to the setting of the project. Third, we only analyzed two project teams with agile methods and two project teams with traditional methods. Due to this limited number, it is possible that we missed subgroups that are relevant, but were not present in our cases.

5.3 Future Research

We only analyzed four teams from two different firms. Due to this limited setting, it was not possible to analyze the influence of different contexts on the formation of subgroups in detail. However the context could have a huge influence on the activation of certain faultlines. Future research could further address which faultlines dominate others and whether these could be affected by management practices. Studies could examine how far agile methods could reduce location-based faultlines in distributed teams in detail.

The size of the teams that we analyzed has been between 12 and 19. Future research could address this by varying the team size. Due to closer collaboration in smaller teams, it could be the formation of subgroups differs. It could be the case that task-based subgroups do not form in traditional projects, because a specific task is assigned to only one person and not to several. The formation of subgroups could also be different in larger teams. Subgroups, based on special competencies of certain team members [58], could form in large teams.

Up to now, we have only analyzed Scrum as a representative of agile project management methods. Future research could address other ones. For instance, the formation of Subgroups could differ in Pair Programming due to the close collaboration between two team members.

Another possible area for future research could be related to the question how subgroups are resolved in agile methods and in traditional methods. We have found that team 3 has breakfast together every Monday. One could analyze whether such team-building events are effective in resolving subgroups. Approaches to resolve subgroups could have different influences in agile and traditional projects. An event to get to know all team members might be useful in a traditional project, but not in an agile project with Scrum, because all team members know each other from the daily stand-up meeting.

6. Conclusion

This paper was motivated by a need to understand groups within agile and traditional IT projects. The results of the conducted case studies show that the formation of subgroups differs between the two types of projects. We find that previous ties leads to the formation of subgroups in agile methods whereas task assignment leads to strong subgroups in traditional methods.

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Appendix C – Publication P2

“Do I Want to Have Losers In My Team?” – A Quantitative Study of Learning from IT Project Failure

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Abstract

This paper is motivated by a lack of research on the learning from failed IT projects of IT professionals. It remains unclear whether they learn from failed projects and conduct more successful projects in the future. We investigate this research gap with a large quantitative dataset from a German IT service provider. We find that IT professionals learn from failed projects and can leverage this knowledge in the future. Therefore, they should not be seen as “losers”, but as a valuable human resource. Our research contributes to the limited research of learning from failure in IT literature. We show that results that have been obtained in other domains are transferable to the IT domain. Our research is limited by the circumstance, that our dataset comes from only one IT company. This is the first paper that analyzes learning from failure of IT professionals and their performance in future projects.

1. Introduction

IT projects have a quite high failure rate. According to studies by The Standish Group [1], the failure rate of IT projects is higher than 60%. Although the IT market has increased its maturity [2, 3], the failure rate has not significantly decreased over the past decade [1]. It is estimated that the cost of failed IT project is about \$3 to \$6 billion every year [4, 5].

Due to the high failure rate, IT employees experience project failures quite often. Failed projects not only have a financial impact, but also create negative emotions among the employees [6]. Despite these negative effects, failed IT projects might also have a positive effect. IT employees might learn from failed projects and leverage the gained knowledge in future projects. Learning from failed IT projects on the organizational level has already been examined for instance by Ewusi-Mensah and Przasnyski [7], but they focused on organizational learning and not on the learning of individual project members. There are studies in management literature that focused on learning from failure on the individual level [6, 8-11]. For instance, Shepherd, Patzelt [10] analyzed learning from failed research project.

However, it remains unclear whether these results are transferable to the IT domain. In order to learn from a failure, it is necessary that a certain attention is drawn to the failed project [12]. The failure rate of IT projects is much higher than in most other domains. Therefore, it is possible that IT employees do not pay a lot of attention to failed projects, because they are a common thing.

Additionally, it remains unclear whether IT employees can leverage the gained knowledge in future IT projects. It is possible that they have learned from a failed project, but as IT is in constant change and new technologies and trends arise quickly [13], they cannot leverage the gained knowledge in future projects.

In order to address this research gap, we aim to answer the following research question: *Do IT professionals learn from failed projects and perform better in future projects?*

We answer this question with a unique data set from an IT service provider, which is called ALPHA due to confidentiality reasons. They granted us access to data from their internal project controlling and human resource management systems. We gained extensive data on all 36,413 projects conducted by ALPHA between January 1995 and April 2014 and

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information on more than 8,000 IT employees that worked on these projects during that period.

This paper is structured as followed. First, we present background information on learning from failure and on the success of IT projects. This is followed by the development of the hypotheses that are subsequently examined. Then, we outline the dataset, the variables and the chosen research method. In the next section, we present the results of our data analysis. Finally, the theoretical and practical implications as well as limitations and possible future research are discussed. The paper ends with a short conclusion.

2. Theoretical Background

2.1 Learning from Failure

There are many different definitions of learning which focus on various aspects like change, detecting and correcting errors, improvement, knowledge or understanding [14, 15]. For this paper we adopt the definition that learning is the development of insights, knowledge, and associations between past actions and the effectiveness of those on future actions [15]. This definition focuses on the relationship between the past, present and future and defines learning as a process and not as a single event. Learning does not occur instantly, but over time [16]. During a learning process, experience or provided information is converted into knowledge [14].

It is possible to distinguish two different forms of learning, namely learning through teaching and learning by experience. Teaching is an organized from of learning and based on controlled settings [17, 18]. It can occur in many forms, such as training, mentoring or coaching and normally occurs separated from the normal working place [18, 19]. Learning by experience occurs during normal working tasks [19, 20]. Studies argue that employees only learn abstract knowledge from training, but lack the practical experience [17, 21].

Learning from failure is a special form of learning by experience. In general, learning is possible from failure as well as from success [22]. Success tells what to do and failure what not to do [23]. However, learning from success has a drawback. A continuous series of successes motivates a firm to become specialized in these successful operations, but this makes the firm inflexible [24, 25]. Therefore, learning from repeated successes makes failure in the future more likely [24]. A failure forces the involved individuals to critically examine the actions which lead to the failure and therefore enhance a broader understanding of the underlying relationships that have led to the failure [9, 26]. This gained knowledge leads to a change of behavior in similar situations in the future, which might help to prevent a failure [26, 27].

Many studies suggest that failure is a better source for learning than success [9, 27, 28]. Due to this, failure should be seen as an opportunity not as something to be embarrassed of [6, 7, 26]. If the errors are not hidden, but carefully analyzed by the involved individuals, it is possible to prevent future mistakes [7]. To make this possible, it is important that a positive learning environment with psychological safety should be established in order to enable learning from the failure [29].

Previous research on learning from failure can be categorized whether learning is considered at the organizational level or at the individual level.

On the organizational level, for instance, Baumard and Starbuck [24] analyzed 14 failures in a large European telecommunication company. They found that companies, in general, learn little from failures. Either learning does not take place or the wrong things are learned. Research on learning from failure of IT projects is limited. A rare example is Ewusi-Mensah and Przasnyski [7] that analyzed whether companies learn from failed information systems development projects. They found that most companies do not learn from their failed projects. Another example is Kasi, Keil [30] who analyze the usage of post mortem evaluations after project failures. They find that post mortem evaluations are only seldom conducted due to limited learning capabilities in most IT organizations.

On the individual level, to the best of our knowledge, no study analyzes whether IT professionals learn from failed projects and leverage their knowledge in the future. There is one paper, but it analyzes learning o IT professionals from failure only on a conceptual level [31]. There are several studies in management literature that focus on learning from failure [6, 8-10]. These studies analyze professionals from scientific research [9, 10] as well as entrepreneurs [6]. For instance, they focus on how individuals cope with failure and learn from them [10] or on the influence of the speed of project termination [9]. However, none of these studies analyzes whether employees can leverage the gained knowledge in future projects or possible failure situations in the future.

This brief overview on the theoretical background of learning from failure shows that there is little research on learning from failure within the IT domain, especially on learning from failure on the individual level. The IT domain is different from other domains. It is characterized by quickly changing developments [32]. Additionally, due to the high failure rate, IT employees quite often face project failure. Therefore, it remains unclear, if project failure still evokes negative emotions and therefore leads to learning or if it is just taken as normal and not considered further. Furthermore, it shows that current literature on learning from failure has not yet analyzed whether it is possible to leverage the gained knowledge in future projects.

Due to these points, it remains unclear whether the results that have been obtained in other domains are transferable to the IT domain and whether the gained knowledge can be leveraged in the future to improve the success of IT projects.

2.2 Success of IT projects

There are various dimensions of IT project success. For instance, in software development projects, it is possible to use the number of defects, the deviation from the expected effort or whether the schedule was met [33]. Thomas and Fernández [34] identify three categories of IT project success: project management (On-time, On-budget, Sponsor satisfaction, Steering group satisfaction, Project team satisfaction, Customer/user satisfaction, Stakeholder satisfaction), technical (System implementation, Met requirements, System quality, System use) and business (Business continuity, Met business objectives, Delivery of benefits).

If an external IT vendor is conducting the project, the success of the IT project is mostly determined by the financial performance of the IT project. Previous studies have used the absolute profits of each project [35-37], the price of the contract [38] and the profitability of the project [39, 40].

The success of IT projects is a complex construct and is influenced by many different factors [34, 41]. One important factor that influence the success of the IT project is the team and its members [33, 42, 43]. Each team member has different attributes, such as work history, knowledge, gender or beliefs [33, 42, 43]. The composition of the team influences the performance of the team [33, 42, 43].

2.3 Hypotheses

We argue that project failure triggers learning among IT employees. They develop knowledge about the causes of the failure and about how to react in the future in similar situations. IT employees are normally part of a larger project team. They can leverage the gained knowledge in two ways: first, directly by leveraging the gained knowledge during their work and, second, indirectly by sharing the gained knowledge and experience with other team members. In general, due to knowledge sharing within the team [44], the whole project profits from knowledge that has been gained by one person that has experienced a failure in the past. Therefore, we formulate the following first hypothesis:

H1: An IT professional that has experienced a failure contributes positively to the success of projects in the future.

If there are more team members who have experienced a failure in the past, we can expect that the performance of the project increase more compared to a team with only a small ratio of team members that experienced a failure. First, it is likely that the reason for failure has been different from team member to team member. Therefore, there should be a broader variety of knowledge within the team. Second, not a single team member that has to pass on the gained knowledge, but several ones can share their experiences. Therefore, there is no bottleneck. Due to this, we formulate the following second hypothesis:

H2: An increased ratio of IT professionals that experienced a failure in the past increases the success of projects.

3. Research Method

3.1 Data set

The quantitative data, which is the basis for our analysis, was collected from a German IT service provider. This company generates a large proportion of its revenue with consulting projects and to a minor extent by offering other ITO services such as standard software development and hosting. Due to reasons of confidentiality this company will be named ALPHA. ALPHA granted us full access to their project controlling system, where we were able to extract 36,413 projects that were conducted between January 1995 and April 2014 with detailed metadata, like project revenue, profit, contract type, information on the customer and so forth. Since this data is extracted directly from the system and also used for billing purposes, the quality of the dataset is particularly high and not subject to recall bias, which is sometimes mentioned regarding surveys, interviews and case studies [38]. Additionally, we were able to gather data of more than 8,000 employees from the internal human resource management system, which enabled us to identify and keep track of employees that were working on these projects. This linkage was especially necessary for observing the individual learning curve of the involved IT professionals.

We filtered the raw data to eliminate internal projects and discarded projects with incomplete data. To remove outliers, we performed a 5% trimming algorithm according to Eriksson [45] on the variable project performance, which is a common approach in empirical ITO vendor studies [39, 46]. The final dataset comprised 19,004 projects. To additionally account for the effect of outliers we log-transformed some of our variables [47].

3.2 Variables

The dependent variable of our analysis is the performance of the project. The clients' project performance can be measured according to the adherence of costs and time estimates, as well as on the quality of project output and realized benefits [33]. External service provides measure their performance with a different approach. Studies on vendor's project performance therefore focus on financial measures, like the price of the contract [38] or the absolute project profits [35-37]. The metric that we have adapted is *project profitability* [39, 40] due to its relative characteristics that allows the comparison of different sized projects. Due to confidentiality reasons, it has been multiplied with a constant factor. This is a common approach to anonymize profitability [39, 40].

The independent variables in our analysis captures whether there has been experience with failure in the past. We use two different variables for this purpose.

Member with failure experience. We use a binary variable for measuring whether a member of the project has experienced a major failure in the past. The extent of failure needs to be great in order for negative emotions to be generated that will trigger the learning process [8, 9]. We defined major failure based on two criteria. First, the project profitability has to be minus 20% or below. Even if the rate of return may be very low this might not be classified as a failure, if only a small amount of money is involved. Therefore, we chose a minimum loss of 10.000 € as the second criteria. This amount is roughly the revenue an employee generates in one month. Since the values of these conditions are arbitrarily chosen, we conducted robustness checks that confirm our results.

Ratio of Failure Experience. It measures the ratio of project members that have experienced a major failure in the past. The definition of major failure remains unchanged. Accordingly, if the ratio is zero this corresponds to a team where nobody has ever experienced a failure before.

We employ the following control variables in our analysis.

Client Experience within Team. Previous studies have found that client experience has a significant influence on project performance [35, 37, 40, 48]. In general, client experience can be approximated in several ways. It can be measured as a binary variable, where the variable indicates whether there has been prior interaction [35, 37], as the number of prior projects [40] or as the volume of prior projects [49]. We used the sum of hours worked for that customer within the team.

Project Size. According to Barki, Rivard [50] the size of a project has a considerable influence on the risk of the project. Previous studies have found that it significantly increases the project performance [35, 37, 39, 40]. In this analysis, project size is approximated by the revenue of the project.

Project Duration. Longer projects are harder to specify and to forecast [35, 38]. It is also more likely that there are changes during the project [38, 50]. Therefore, the performance of long running projects should be lower [41]. Project duration has also been included as a variable in other project performance studies [35, 37-40]. In this study, project duration is approximated by the number of days that the project ran.

Team Size. A large project team increases the risk of underperformance because of coordination problems [35] and therefore it might have a negative influence on the profitability of the project. However, it could also be the case that team size has a positive influence on profitability, if the team is too small and overworked [35]. Due to its influence, team size has also been used by other studies on project performance

Table 1. Descriptive Statistics

	Mean	SD	1)	2)	3)	4)	5)	6)	7)	8)
1) Project Profitability	0.31	0.58	1.00							
2) Member With Failure Experience	0.68	0.47	0.01	1.00						
3) Ratio of Failure Experience	0.52	0.42	-0.03	0.85	1.00					
4) Client Experience	15,361	25,132	-0.01	0.41	0.36	1.00				
5) Project Size	96,942	713,951	0.16	0.10	-0.06	0.14	1.00			
6) Project Duration	211	248	0.06	0.20	0.10	0.21	0.59	1.00		
7) Team Size	4.29	6.10	0.11	0.39	0.15	0.39	0.47	0.42	1.00	
8) Contract Type	0.41	0.49	-0.04	0.21	0.24	0.26	-0.15	-0.06	0.13	1.00

[35, 37, 39, 40]. In our analysis, team size is defined as the number of different employees that have worked on the project.

Contract type. There are two basic types of IT outsourcing contracts: fixed price (FP) and time & material (TM) [37, 51]. In FP contracts, the ITO vendor agrees to deliver a predefined result and gets compensated with a certain fee [35]. TM contracts are different, because the billing is based on the agreed hourly rate and the working hours that the ITO vendor invested [35]. The contract type has been used as a control variable by several studies [35-37, 39, 40]. It is coded as a binary variable, where 0 stands for a TM contract and 1 for a FP contract.

Year of project start. A dummy variable for the year of the project start has been included in the analysis. This variable captures year specific effects such as exchange rate fluctuations, inflation and business fluctuations [35, 39].

3.3 Data Analysis

Table 1 shows the mean and the standard deviation (SD) of numerical variables and the correlation matrix. In order to reduce skewness, we log-transformed client experience, project size, project duration and team size [47].

To detect multi-collinearity, we employed the variance inflation factor (VIF) [52, 53]. The values of the VIF lie between 1 and infinity and values between 5 and 10 can be used as a threshold to decide whether a problematic amount of multi-collinearity is present or not [52]. We obtained values clearly below 2 and therefore multi-collinearity should not be an issue.

The correlation coefficients between *Client Experience within Team* and the two independent variables as well as between *Member with failure experience* and *Team Size* are moderate, but due to low VIFs should not cause problems.

To test the hypotheses, we construct multiple linear regression models. The first model only contains the control variables. The second model will analyze the first of our two proxies for influence of failure experience, namely *Member with Failure Experience*. The third model analyze the second proxy, *Ratio of Failure Experience*. We have used this approach with two different variables because of robustness reasons.

As our data set contains several projects for the same customer, we have to correct for panel data [54, 55]. We conducted the Hausman tests for each model to choose between a fixed-effect models and a random-effect model [56]. The test shows that a fixed-effect model should be used in all three models, as the p-values are clearly below 0.05.

4. Results

The results of the multiple regression models are presented in table 2. First, there is a base model that only contains the control variables.

Table 2. Results Of The Regression Analysis

Dependent variable: Project profitability (anonymized)			
Variable	**Base Model**	**Model 1**	**Model 2**
Member with Failure Experience		0.040 *** (0.012)	
Ratio of Failure Experience			0.029 * (0.012)
log(Client Experience)	0.010 *** (0.002)	0.009 *** (0.002)	0.009 *** (0.002)
log(Project Size)	0.066 *** (0.004)	0.066 *** (0.004)	0.066 *** (0.004)
log(Project Duration)	-0.062 *** (0.005)	-0.062 *** (0.005)	-0.062 *** (0.005)
log(Team Size)	-0.151 *** (0.007)	-0.157 *** (0.007)	-0.151 *** (0.007)
Factor(Contract Type)	0.062 *** (0.010)	0.060 *** (0.010)	0.060 *** (0.010)
Factor(Year)	significant	significant	significant
Adj. R-squared	4.68%	4.74%	4.71%
F-value	46.82 ***	45.19 ***	44.87 ***
Hausman test: *Chisq* (*p-value*)	126.60 (< 2.2e-16)	138.07 (< 2.2e-16)	139.87 (< 2.2e-16)
Standard errors are reported in brackets Significance: *** = significant at the 0.1% level; **= significant at the 1% level; *= significant at the 5% level,			

Model 1 analyzes the first hypothesis *H1: IT professionals that experienced a failure contribute positively to the success of projects in the future.* We find that *Member with Failure Experience* has a positive significant influence on project profitability, which supports the first hypothesis H1.

Model 2 analyzes the second hypothesis *H2: An increased ratio of IT professionals that experienced a failure in the past increases the success of projects.* We find that *Ratio of Failure Experience* has a positive significant influence on project profitability, which supports the first hypothesis H2.

When comparing the coefficients of the control variables between the three models, we find that adding *Member with Failure Experience* and *Ratio of Failure Experience* does not significantly change them. This indicates robust models.

5. Discussion

5.1 Limitations

All research is subject to limitations. In the following, we discuss possible limitations of our results.

First, our dataset comes from only one IT company, which might limit the generalizability of our results. This a general problem when dealing with archival datasets [33, 38, 39]. Our results could be influenced by to the way ALPHA deals with project failures. However, discussions with representatives of ALPHA revealed that they have no special way of dealing with project failures in comparison with other IT companies.

Second, our definition of failure (a project with less than -20% profitability and a loss of more than 10.000 €) seems arbitrary. We performed robustness checks, where we varied these figures. The drawn conclusion did not differ from the presented ones. Another issue with the employed definition of failure is that it might not be generally possible to tie failure to such numbers. A project that is not complex might already be seen as a failure, if it does not have a positive profitability. However, due to the large number of projects that have been analyzed, such influences should be cancelled out.

Third, although we find significant relationships, the two variables *Member with Failure Experience* and *Ratio of Failure Experience* only slightly increase the adjusted R-squared in comparison to the base model. To address this issue we employed F tests to analyze whether model 1 and model 2 have a significant higher explanatory power in comparison to the base model. We found that both variables (*Member with Failure Experience* and *Ratio of Failure Experience*) significantly increase the explanatory power.

5.2 Theoretical and Practical Contribution

We contribute to theory in several ways. First, we reject the results of Ewusi-Mensah and Przasnyski [7] and Kasi, Keil [30], which are one of the rare studies of learning from failure in the IT domain. Ewusi-Mensah and Przasnyski [7] analyzed the learning from failed information systems development projects and found that organizations do not learn from them. Kasi, Keil [30] analyzed the usage of post mortem evaluations after project failures and found that post mortem evaluations are only seldom conducted due to limited learning capabilities in most IT organizations. However, we found that IT employees learn from failed project and tend to perform projects that are more successful in the future. A possible explanation for these opposing results could be the different levels of analysis. We analyzed learning on the individual level, but Ewusi-Mensah and Przasnyski [7] and Kasi, Keil [30] analyzed it on the organizational level. Another possible explanation could be that Ewusi-Mensah and Przasnyski [7] and Kasi, Keil [30] based their conclusions on the retrospective actions that companies conducted after a failed project. Such actions might be a good way to learn from a failed project, but learning from failure also occurs in an unstructured and informal way among the involved team members.

Second, we extend research on the learning of individuals after a failure to the IT domain. These studies have been conducted in settings like research projects or entrepreneurial activities [6, 8-10]. The IT domain is different than other domains. It is characterized by quickly changing developments [32]. Furthermore, due to the high failure rate, IT employees quite often face project failure [1]. Therefore, it remains unclear, if project failure evokes negative emotions among IT employees, which are necessary to trigger the learning process [8, 9]. Our results suggest findings that haven been obtained in other domains [6, 8-10] are transferable to the IT domain.

Third, we show that knowledge that has been gained through learning from failed IT projects can be leveraged in future projects and significantly improves the performance. This has not been done in other studies on learning from failure on the individual level [6, 8-11]. This is an important aspect, because having gained knowledge through learning from a failure is one thing, but IT managers are more interested in the question whether future projects perform better because of the gained knowledge.

Fourth, our results show that it already has a positive effect, if only one member of the team has experienced a failure. This member seems to spread its knowledge to other team members which then are able to perform better in certain situations [44]. Additionally, our results show that the higher the ratio of team members with failure experience, the higher the performance of the project. This might be due to the two following reasons. First, it is likely that the reason for failure has been different from team member to team member. Therefore, there should be a broader variety of knowledge within the team. Second, not a single team member that has to pass on the gained knowledge, but several ones can share their experiences, which prevents a bottleneck of knowledge sharing.

We contribute to practice in several ways. First, our results suggest that IT employees that have experienced a failure in the past should be seen as a valuable resource and not as “losers”. They should not be devalued or generally blamed for a failure.

Second, IT managers should create an atmosphere for learning for the involved IT professionals after a failed project. Carmeli and Gittell [29] show that a positive learning environment with psychological safety intensifies learning from failure

Third, our results suggest that it is advisable to staff projects with individuals that have experienced failure in the past in order to increase the project success.

5.3 Future Research

We analyze learning from failure on the individual level only indirectly through the performance of future projects. Future research could analyze learning from failure directly based on individual performance indicators.

Another possible direction for future research could be the consideration of the time since the failure occurred. According to Argote, Beckman [57] acquired knowledge gets outdated quickly in organization setting. Therefore, it is likely that the influence of failure experience decreases with time.

Our results show, that it has a positive effect on the project performance, if one team member has experienced a failure in the past. Furthermore, they show that the performance increases, if more team member have a failure experience. Future research could analyze the influence of different configurations of team members with failure experience and team members with no failure experience. We find that the ratio of team members that have experienced a failure in the past significantly increases the performance of a project. Our analysis assumes a linear relationship. Future research could relax this assumption and perform a non-linear analysis. It is possible that the relationship has an inverted U-shape or reaches a plateau after a certain ratio.

Another possible direction for future research could be to analyze whether different types of personalities cope differently with the failure and therefore differ regarding learning from failure [58].

Finally, future research could analyze if persons within the social network of an employee that experienced a failure also learn from this failure. Kim and Miner [59] have analyzed whether organizations learn from failures of other organizations. They found that learning occurs and that it is increased if accessibility to the failure and applicability of the failure to the own business are given.

6. Conclusion

This research was motivated by a lack of research on learning from failure of IT employees. We employed a unique dataset from a German IT consulting company and found that IT employees learn from failed IT projects and leverage this gained knowledge in future projects. We contribute to theory by extending previous research on learning of individuals in other domains to the IT domain. Furthermore, we contribute to practice by showing that IT employees that have experienced a failure in the past are a valuable resource and should not be blamed or devalued or be seen as “losers”. IT managers should even think about staffing IT projects with employees that have experience with failure.

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Appendix D – Publication P3

The Dual-sided Effect of Project Failure on IT Professionals

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ABSTRACT
The effects of project failure on IT professionals have not received much attention in IT research. A failed project evokes negative emotions and therefore could trigger turnover, which has negative influences from the perspective of IT human resource management. However, the failure of IT projects could also have positive influences as professionals might learn from the failed project. This paper focuses on analyzing this dual-sided effect of project failure on IT professionals. We develop hypotheses that will be tested with a large data set from an IT service provider in future research. We expect to contribute to theory by analyzing whether project failure triggers turnover and by analyzing whether IT professionals learn from failed projects and perform better in the future.

Keywords
Project Failure; Learning; Turnover

1. INTRODUCTION
IT projects have a quite high failure rate. According to a report by The Standish Group [42], the rate of unsuccessful projects is higher than 60% and has not significantly decreases over the past decade, although the maturity of the IT market has increased [30; 32]. It is estimated that IT project failures create cost of $3 to $6 billion every year [19; 34].

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Most of the literature on IT project failure has concentrated on identifying factors that lead to failure (e.g. Cerpa and Verner [4], Keil [17], Pankratz and Basten [28], Yeo [45]). The focus has mostly been on how to prevent it and therefore project failures have been seen as something negative [10].

Failed projects not only have a financial impact, but also have negative effects on the project members. They create negative emotions, which could be a shock event that triggers turnover based on the unfolding model of voluntary turnover [20; 36]. This relationship has not yet been analyzed. Turnover is problematic for IT organizations, as it is difficult to find a replacement due to the high demand for skilled IT professionals [39; 43]. Additionally, turnover creates high costs [5; 40; 41].

However, IT research has not yet focused on the possibility that project members might learn from failed projects and leverage these learnings in future projects. Learning on the organizational level has been considered by Ewusi-Mensah and Przasnyski [8], but they did not focus on individual project members. However, there are studies in management literature that focused on learning from failure on the individual level [35-38].

As it can be seen, project failure has a dual-sided effect on IT professionals from the perspective of IT human resource management. On the one hand, it could lead to turnover of IT professionals, which has negative effects, but on the other hand, professionals might learn from the failed project. This has not yet been analyzed in IT literature. Therefore, we pose the following research question:

What is the relationship between project failure and turnover as well as learning from failure on the individual level?

We plan to answer this question with a unique data set from an IT service provider, called ALPHA. They granted us access to data from its internal project controlling and human resource management systems. We gained extensive data on all 36,413 projects conducted by ALPHA between January 1995 and April 2014 and on all 8,180 IT professionals that worked for ALPHA during that time period.

The remaining sections of the paper are structured as follows. First, we present background information on learning from failed projects as well as on turnover of IT professionals. This is followed by the development of the hypotheses that will be analyzed in future research. We then outline our dataset in detail und present the planned analysis approach. Finally, the expected contributions are discussed and the paper ends with a conclusion.

2. THEORETICAL BACKGROUND

2.1 Learning from Failure

Project failure can be divided into project management failure, where the project fails to meet cost, time or quality, and into product failure, where the outcome of the project fails to meet the expectations [3; 28; 42]. As previously mentioned, quite a significant share of IT projects fail which creates high costs [19; 34; 42].

Most of the literature on IT project failure has concentrated on identifying factors that lead to failure (e.g. Cerpa and Verner [4], Keil [17], Pankratz and Basten [28], Yeo [45]). This focus on hindering project failure creates a negative view. However, a failure might not always be a total loss and offers the opportunity to learn from it [8; 10].

For instance, Ewusi-Mensah and Przasnyski [8] argue that organizations should keep record of their failed projects and try to understand what went wrong. According to Grainger, McKay and Marshall [10], project failures should be considered in a broader context, as the learning from a failure could be the reason for a subsequent successful project. However, the mentioned studies focus on the organizational level and did not consider the learning from project failure on the individual level.

Learning from failure on an individual level has been analyzed in management literature [35-38]. It has been found that failure evokes negative emotions, but depending on how individuals cope with these emotions leads to learning [35-38]. Members of the failed project start thinking about different actions that could have been taken and their influence on the project [38]. By doing so they develop capabilities and knowledge about how to react in similar situations in future projects [7; 38].

2.2 Turnover of IT professionals – The Unfolding Model of Voluntary Turnover

Turnover is defined as "voluntarily leaving an IT job for an alternative IT job with a different employer" [15]. Turnover is problematic for IT organizations, as it is difficult to find a replacement due to the high demand in the IT labor market [39; 43]. Additionally, turnover creates high costs through recruiting and training, but also through the disruption of organizational processes [5; 40; 41]. There are several studies that estimate these costs to be between 90% and 700% of the annual salary of an IT professional [1; 18].

The unfolding model of voluntary turnover after Lee and Mitchell [20] is a theory that has gotten more popular in recent turnover research [2]. It focuses on the decision process of turnover and argues that a shock event often acts as a trigger. Shock events can either be (1) positive or negative, (2) expected or unexpected and (3) originate on the organizational or personal level [21]. Several decision paths that can be taken by IT professionals have been proposed by Lee and Mitchell [20].

This kind of turnover theory has been mentioned by several IT as well as general turnover related literature reviews as a possible area for future research [2; 13; 16]. According to Joseph, Ng, Koh and Ang [16] IT turnover research should focus on understanding events that trigger turnover.

Recent IT turnover literature has employed and contributed to the unfolding model of voluntary turnover. Niederman et al. [27] have found additional decision paths that are especially relevant to the IT domain. Mourmant and Gallivan [23] focused on the influence of personality on taking different decision paths. There are a few studies that employed the unfolding model of voluntary turnover to analyze the turnover of IT professionals that have the aim of founding an own company [24-26].

3. HYPOTHESES

The aim of this article is to examine the dual-sided effect of project failure on IT professionals.

A project failure could be a shock event after the unfolding model of voluntary turnover of Lee and Mitchell [20]. It has been shown that project failures evoke negative emotions, such as frustration, disappointment, depression, anger or doubts about one's work [35-38]. These emotions should be strong enough to trigger the decision processes of turnover. Employing the categorization of Lee and Mitchell [20], a project failure is a shock that is (1) seen negatively by the individual, (2) mostly unexpected, as individuals normally do not expect the failure at project start, and (3) originates on the organizational level. Therefore we formulate the following hypothesis:

H1: Project failure increases the probability of turnover among the members of the team that worked on the project.

A project failure enables members of the project to learn from the failure to improve their knowledge for future projects [8; 35-38]. It has even been claimed that the possibility to learn from failure is higher than from success [29; 31]. The reason for this is that a success does not attract enough attention to think about the causes for this positive outcome [7]. Project members of a failed project can leverage their gained knowledge and tend to conduct on average more successful projects regarding budget, time and quality in the future [38]. Therefore, the following second hypothesis is formulated:

H2: Team members that have experienced a project failure conduct more successful projects in the future.

4. METHOD

4.1 Data Sample

In order to examine these hypotheses, we extracted data from the internal project controlling and human resource management systems of a large German IT service provider, which is called ALPHA due to non-disclosure reasons. Directly accessing quantitative data from internal systems is not subject to recall bias, which could be a problem in case studies and surveys [9; 14]. ALPHA granted us access to all 36,413 projects conducted between January 1995 and April 2014. Additionally, we collected information on all of its 8,180 IT professionals that worked during that time period for ALPHA.

We collected information about each project such as the project profitability, the contract type, the team size, the number of interactions with a client as well as within an industry, the business climate based on a recognized index, the project start, the project size, the industry of the client and the project duration. To link each IT professional to the projects, we extracted the information which professional worked how many hours for which project on which day. Detailed Information about the yearly performance review, the planned and attended trainings, the home base, the educational background, the organizational unit, the job level, the recruitment date and the turnover date of the IT professionals have as well been collected.

4.2 Measures and Planned Data Analysis

For analyzing the described hypotheses, we created subsets of the previously described overall dataset. The measures of these subsets are described in table 1 and 2. We plan to analyze the hypotheses H1 and H2 with the two described subsets. As turnover is a dichotomous variable, H1 will be analyzed with a logistic regression model. H2 will be analyzed with an ordinary least squared regression model.

Table 1. Measures for analyzing H1

Dependent variable	• **Turnover**: This information has been directly extracted from the human resource management systems and therefore allows the analysis of actually occurred turnover, which is an under-researched area [16; 22].
Independent variables	• **Project failure experienced**: Projects with a high negative profitability and a certain amount of loss are used as a proxy for this measure, because they can be seen as a failure for ALPHA. This measure captures whether team members have experienced a project failure in the past. • **Control variables**: Several factors that have been found to influence turnover are employed as control variables, such as age, gender, organizational tenure, training and educational background [16; 22].

Table 2. Measures for analyzing H2

Dependent variable	• **Project profitability**: This measure has been extracted from the project controlling systems of ALPHA.
Independent variables	• **Project failure experienced:** Projects with a high negative profitability and a certain amount of loss are used as a proxy for this measure, because they can be seen as a failure for ALPHA. This measure captures whether team members have experienced a project failure in the past. • **Control variables**: Research on ITO vendor profitability has revealed several factors that have an influence on profitability, such as project size, duration, team size, client knowledge, industry knowledge [12; 33]

5. EXPECTED CONTRIBUTION

We expect to contribute to theory and practice in various ways. According to Joseph, Ng, Koh and Ang [16] the unfolding model of voluntary turnover and the identification of shock events has not yet received much attention in IT turnover literature. In recent years, it has gotten more popular and has been employed by several studies [23-27], but they did not focus on project failure as a possible shock event.

An expected practical contribution is that project failure could trigger turnover and that IT managers should intervene to prevent the turnover of key IT professionals. It has been shown, that retention actions should be taken rather quickly, because professionals that experienced a shock tend to leave faster than professionals with a low satisfaction [21].

Another theoretical contribution will be the understanding of project failure as a learning opportunity for IT professionals. This has not received much attention in IT literature. We expect to shed light into the relationship between project failure and learning from this failure of IT professionals.

IT professionals should be carefully selected for risky projects. Professionals that already have a low organizational commitment and high levels of stress could be indirectly forced into turnover. Additionally, learning from failure should not always be experienced by the same people, because otherwise they do not have the opportunity to exploit their learnings in less riskier projects.

After analyzing the described hypotheses, future research could analyze the underlying relationships in more detail. This could be done with explorative qualitative studies. An interesting research topic could be to analyze how employees could learn from project failures without having to be a member of the failed project. Additionally, the personality of the IT professionals could be taken into account, which has been found to significantly influence job outcomes [6; 11; 44]. Shepherd, Haynie and Patzelt [36] suggest that employees differently cope with failures.

6. CONCLUSION

Project failure has mostly been considered as a negative event in IT literature. We extend this view and argue that failure could have a dual-sided effect. It should increase the probability of turnover among the members of the project, but on the other hand the project members have the opportunity to learn from the failure and increase their contribution to the performance of future projects. We expect to shed light into these relationships through the outlined future research.

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Appendix E – Publication P4

MIS QUARTERLY EXECUTIVE

Strategies for Retaining Key IT Professionals[1]

Retaining IT professionals is a key and challenging issue for IT managers. There is no "silver bullet," and retention actions must be tailored to the profile of each employee the organization wants to retain. IT professionals have different reasons for changing jobs, determined by their career goals, relationships within the organization and current attitude to the job. We show how IT employees can be classified into seven types and describe the retention actions that will work best for each type.[2, 3]

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Retaining IT Professionals is a Key Issue for IT Managers

Turnover of IT professionals poses several challenges to IT organizations. First, finding a successor to someone who has quit is often difficult due to the high demand for skilled IT professionals in the global IT labor market. As IT managers are well aware, programming is one of the most sought after professions.[3] Moreover, high demand for skilled and specialized IT professionals is predicted to continue to increase in the future.[4]

Second, it is not only difficult but costly to find a skilled replacement for an IT professional who has quit. Turnover creates direct costs, such as recruiting and training, as well as indirect costs through the disruption of organizational processes. Studies have estimated these costs to be between 90% and 700% of the annual salary of the replacement IT professional.[5,6] One reason for such high costs is the time it takes for a new IT professional to become fully productive, which one study estimated to be around 18 months.[7] Because IT professionals are a scarce resource, and their turnover is costly, IT managers should focus on reducing turnover and retaining existing employees.

Generally, the retention process evolves as follows. Weak signals sent by an employee or the work environment provide clues to the IT manager that there is a probability of an IT employee quitting. If the probability of leaving is above a certain level, the manager can decide whether to make an effort to retain the employee; it may not be cost effective or prudent to retain every

1 10.17705/2msqe.00003
2 Fred Niederman, Michelle Kaarst-Brown, Jeria Quenesbery and Tim Weitzel are the accepting senior editors for this article.
3 Torpey, E. "Finding hot jobs: Using data to locate career opportunities," *Career Outlook*, U.S. Bureau of Labor Statistics, December 2016, available at https://www.bls.gov/careeroutlook/2016/article/pdf/hot-jobs.pdf.
4 Strauss, K. "Predicting The Fastest-Growing Jobs Of The Future," *Forbes.com*, November 7, 2017, available at https://forbes.com/sites/karstenstrauss/2017/11/07/the-fastest-growing-jobs-of-the-future/#61c1a4c3727a.
5 Allen, D. G., Bryant, P. C. and Vardaman, J. M. "Retaining Talent: Replacing Misconceptions with Evidence-Based Strategies," *The Academy of Management Perspectives* (24:2), May 2010, pp. 48-64.
6 Kochanski, J. and Ledford, G. "How to Keep Me—Retaining Technical Professionals," *Research Technology Management* (44:3), May 2001, pp. 31-38.
7 Baroudi, J. J. "The Impact of Role Variables on IS Personnel Work Attitudes and Intentions," *MIS Quarterly* (9:4), December 1985, pp. 341-356.

employee who wants to leave. Some potential leavers might just not fit or might be detrimental to the overall "good" of the organization if they remain. However, if the IT manager deems that the employee is a valuable asset to the organization, he or she is duty bound to take appropriate retention actions to prevent the employee leaving.

Choosing the best actions to retain an IT professional who is considering leaving is not straightforward. Cost and time restrictions may preclude using all possible retention actions, and individuals respond differently to the various actions. For example, the employee's current stage of career development might influence his or her reaction to retention actions: younger employees with less experience are often more interested in climbing the career ladder, whereas more seasoned or older professionals might be more focused on achieving a work-life balance to spend more time with family or on hobbies. Furthermore, employees have different motivations for working for their current employer, and these will influence the effectiveness of retention actions. Other factors potentially affecting an employee's reaction to retention actions include relationships with co-workers and attitude to the current job situation.

This article reports the findings of a study that sought to understand the process for retaining IT professionals, focusing on different types of IT employees and corresponding retention actions. During 2008-2012, an exit questionnaire was distributed to 283 employees of a large German IT service provider a few days before they left. From our analysis of the responses, we clustered these IT leavers into seven types of IT professionals, according to their original motivation for joining the business, their relationships with coworkers and supervisor and their reasons for leaving. Next, we identified the best retention actions for each type of leaver based on information from the questionnaires and from interviews with IT managers at the service provider. (The research method is described in the Appendix.)

The seven types of IT leavers and the corresponding retention actions will help IT managers to choose the best options when they become aware that a valued IT employee is considering leaving and thus increase the chances of retaining that employee.

Actions for Retaining IT Employees

IT managers can take various retention actions to persuade an employee to stay with the firm, but because these actions can have different effects, choosing the most effective one is difficult. According to one IT manager we interviewed, it is possible to retain about every second IT employee who is considering leaving, but only if the right retention actions are chosen.

Prior studies and practitioner interviews suggest that the following five actions can help to retain IT employees.[8,9,10,11,12]

1. Financial or Non-financial Compensation

In general, IT employee compensation is influenced by organizational, industry-related and national factors, individual and job-level factors, and strategic decision factors.[13] Financial compensation, such as a pay raise or a bonus, is likely to increase job satisfaction and may be perceived as a form of appreciation.[14,15] However, financial compensation might not be an effective way of retaining IT professionals because they are generally well paid (at least in most

8 Agarwal, R. and Ferratt, T. W. "Recruiting, retaining, and developing IT professionals: an empirically derived taxonomy of human resource practices," *Proceedings of the 1998 ACM SIGCPR Conference on Computer Personnel Research*, Boston, Massachusetts, March 1998, pp. 292-302.

9 Agarwal, R., Brown, C. V., Ferratt, T. W. and Moore, J. E. "Five Mindsets for Retaining IT Staff," *MIS Quarterly Executive* (5:3), September 2006, pp. 137-150.

10 Thomas, S. J. "Exploring Strategies for Retaining Information Technology Professionals: A Case Study," *Walden Dissertations and Doctoral Study*, Walden University, 2015.

11 Bairi, J., Manohar, B. M. and Kundu, G. K. "Knowledge retention in the IT service industry," *Journal of Systems and Information Technology* (13:1), March 2011, pp. 43-65.

12 Joseph, D., Ang, S. and Slaughter, S. A. "Turnover or Turnaway? Competing Risks Analysis of Male and Female IT Professionals' Job Mobility and Relative Pay Gap," *Information Systems Research* (26:1), March 2015, pp. 145-164.

13 Wang, C. and Kaarst-Brown, M. L. "The IT Compensation Challenge: Theorizing the Balance Among Multi-Level Internal and External Uncertainties," *Journal of the Association for Information Systems* (15:3), 2014, pp. 111-146.

14 Agarwal, R., Brown, C. V., Ferratt, T. W. and Moore, J. E., op. cit., September 2006.

15 Joseph, D., Ang, S. and Slaughter, S. A., op. cit., March 2015.

European countries and the U.S.).[16] Non-financial compensation, such as motivational feedback or team building events, also influence retention[17] and can be a cost-effective way of retaining employees. Fortunately, this type of compensation requires minimal effort to implement on the part of the IT manager.

2. Working Arrangements

Special working arrangements may help to retain an IT employee.[18,19] These arrangements include office workspace, the work location of the employee, the possibility of working from home and flexible working hours.[20] Working from home is quite common among IT employees.[21] In general the nature of IT work and the availability of modern communication and collaboration tools make it possible to implement alternative working arrangements for IT employees.

3. Career Development Opportunities

Career development is an important issue for many IT professionals. Promotion is an obvious way to advance an IT employee's career,[22] but providing training can achieve the same end.[23] IT employees' knowledge and skills can rapidly go out of date, leading to professional obsolescence,[24] and training programs are a means of counteracting technical obsolescence. Laying out a long-term career plan for an IT employee can direct career development. Outlining the requirements for achieving the next level of career development can support the employee in achieving career goals and decrease any uncertainty the employee might be experiencing about her or his future at the organization. Empirical findings suggest that career development for IT professionals could mean moving them to non-IT positions in the organization.[25,26]

4. Change of Department

Relationships with coworkers and supervisors can influence retention rates.[27,28] If these relationships are poor or unsatisfactory, assigning an IT professional to a different department within the IT organization with a different supervisor can provide the employee with the opportunity to make a fresh start. The project-oriented nature of IT work makes it relatively easy to switch an employee to a different department.

5. Varying Work Tasks

Performing the same or similar tasks repetitively over an extended period can lead to boredom and possibly hinder an IT professional from reaching his or her full potential. Providing an opportunity to work on a new and challenging task can be motivating.[29] However, what constitutes a challenging task may be different for each IT professional. Some might focus more on technical aspects, like working with a new technology, whereas others might be more interested in and challenged by working in a new domain.

Challenges of Configuring Retention Actions

Finding the right combination of retention actions for IT professionals that IT managers want to keep is challenging. Cost and time restrictions mean it may not be possible to simply try out all the actions to test which of them works. Retention actions incur costs, especially improving financial compensation and providing additional training. Alternative working arrangements, a change in department

16 May 2017 National Occupational Employment and Wage Estimates United States, Bureau of Labor Statistics, March 30, 2018, available at https://www.bls.gov/oes/current/oes_nat.htm.
17 Agarwal, R. and Ferratt, T. W., op. cit., March 1998.
18 Ibid.
19 Niederman, F., Sumner, M. and Maertz, C. "Testing and Extending the Unfolding Model of Voluntary Turnover to IT Professionals," *Human Resource Management* (46:3), August 2007, pp. 331-347.
20 Agarwal, R. and Ferratt, T. W., op. cit., March 1998.
21 24 percent of employed people did some or all of their work at home in 2015, *Bureau of Labor Statistics*, 2018, available at https://www.bls.gov/opub/ted/2016/24-percent-of-employed-people-did-some-or-all-of-their-work-at-home-in-2015.
22 Agarwal, R. and Ferratt, T. W., op. cit., March 1998.
23 Agarwal, R., Brown, C. V., Ferratt, T. W. and Moore, J. E., op. cit., September 2006.
24 Joseph, D. and Ang, S. "Threat of Professional Obsolescence and Mobility Intentions: The Mediating Role of Coping Strategies," *Proceedings of the 16th Americas Conference on Information Systems (AMCIS),* 2010.
25 Reich, B. H. and Kaarst-Brown, M. L. "Seeding the Line: Understanding the Transition From IT to Non-IT Careers," *MIS Quarterly* (23:3), September 1999, pp. 337-364.
26 Reich, B. H. and Kaarst-Brown, M. L. "Creating social and intellectual capital through IT career transitions," *Journal of Strategic Information Systems* (12:2), July 2003, pp. 91-109.
27 Agarwal, R. and Ferratt, T. W., op. cit., March 1998.
28 Agarwal, R., Brown, C. V., Ferratt, T. W. and Moore, J. E., op. cit., September 2006.
29 Niederman, F., Sumner, M. and Maertz, C., op. cit., August 2007.

and assignment to new tasks are also potentially costly because it might not be possible to deploy the IT professional in the most productive way. Although providing career development opportunities through promotion and non-financial compensation are the least costly retention actions, their effectiveness in reducing turnover is uncertain, and they involve some administrative overhead costs.

Moreover, retention actions take time to be effective. When IT managers perceive there is a high probability that an employee will leave, they should implement the most promising retention action first. One of our interviewees highlighted the difficulty of selecting the right retention action:

"The employee actively expressed his dissatisfaction about his current job situation in the yearly performance review. After receiving his notice [to quit], I offered him a promotion, but he did not accept it. Later on, I found out that it was more the tasks he was assigned to than the job level that influenced his decision, but it was too late to convince him to stay. After receiving a notice [to quit], you have to respond quickly." IT Manager

The combination of retention actions needs to be tailored for each IT professional that IT managers want to keep. Each IT employee has different motivations and sets individual goals to achieve during their employment. If employees feel they can no longer reach their goals, they are more likely to consider moving to another company. Retention actions should therefore consider the reasons why an IT professional chose to work for the company in the first place. The choice of retention actions is also influenced by an individual's relationships with coworkers and supervisor.[30,31] Most IT work is conducted in teams where the outcome depends on close collaboration between team members.[32] The employee's attitude to the job situation should also be considered when choosing appropriate retention actions. Attitude is a proxy for job satisfaction, which researchers have found is an antecedent of an intention to leave the firm.[33]

A good working relationship between IT manager and IT employee will help the manager to understand the employee's motivation for joining in the first place, the "fit" of the employee to the organization and the employee's attitude to the job and current projects or tasks. A close relationship will also help the manager to assess if the employee is considering leaving. According to an IT manager we interviewed, close relationships with employees makes it possible to identify roughly 50% to 70% of those who are thinking about leaving. Establishing a close relationship, however, is not always easy. For example, establishing a good working relationship may be difficult if the IT manager and employee are not co-located. The lack of proximity may prohibit direct observations of the employee's behavior during a daily meeting or verbal (and non-verbal) interactions with colleagues.

IT managers should also consider the current organizational context when deciding which retention actions to apply. Assigning an employee to a new department is only possible if a department is willing and able to offer a position. Moreover, retention actions differ in terms of how easy they are to implement and how long they remain effective. Improving financial compensation, for example, is easier to action than creating special working arrangements that meet the employee's unique private-life demands, but financial rewards might not remove the reason for the employee's dissatisfaction.

Seven Types of IT Leavers and Possible Retention Strategies

From our analysis of the questionnaires completed by employees of the German IT service provider just before they left, and from interviews with IT managers at the provider, we have classified these IT leavers into seven types of IT employees. Our classification is based on employees' original motivations for joining the firm because we see this as a proxy for career goals and employee relationships

30 Agarwal, R. and Ferratt, T. W., op. cit., March 1998.

31 Agarwal, R., Brown, C. V., Ferratt, T. W. and Moore, J. E., op. cit., September 2006.

32 Vidgen, R. and Wang, X. "Coevolving Systems and the Organization of Agile Software Development," *Information Systems Research* (20:3), September 2009, pp. 355-376.

33 Joseph, D., Ng, K.-Y., Koh, C. and Ang, S. "Turnover of Information Technology Professionals: A Narrative Review, Meta-Analytic Structural Equation Modeling, and Model Development," *MIS Quarterly* (31:3), September 2007, pp. 547-577.

Table 1: Seven Types of IT Leavers

Leaver Type	Original Joining Motivation	Relationships [34]	Reasons for Leaving
A: "I Have No Real Stock Here"	• Recommendation from friend/ colleague	• Average relationship with coworkers • Slightly poorer relationship with supervisor	• Insufficient non-monetary recognition • Lack of career opportunities • Dissatisfaction with general work environment • External job offer
B: "This is the Wrong Job for Me"	• Opportunity to work on challenging tasks • Size and location of company	• Average relationship with coworkers • Good relationship with supervisor	• Dissatisfaction with general work environment • Lack of career opportunities • Poor fit between employee and assigned task
C: "The Job Does Not Fit with My Spouse's or Partner's Needs"	• Recommendation from friend/ colleague • Size and location of company	• Very good relationships with coworkers and supervisor	• Dissatisfaction with work-life balance • Dissatisfaction with general working environment • Personal triggers related to private life
D: "I Do Not Like It Here"	• Recommendation from friend/ colleague • Company culture • Size and location of company	• Very poor relationships with coworkers and supervisor	• Poor working relationship with supervisor • Insufficient non-monetary recognition • Dissatisfaction with general working environment • Lack of career opportunities • Dissatisfaction with work-life balance

34 Relationships for each type were assessed against the average rating of relationships across all 283 IT leavers.

Table 1: Seven Types of IT Leavers (continued)

Leaver Type	Original Joining Motivation	Relationships[33]	Reasons for Leaving
E: "I Need Something New"	• Recommendation from friend/ colleague • Opportunity to work on challenging tasks • Company culture • Career advancement	• Very good relationships with coworkers and supervisor	• Lack of career opportunities • Dissatisfaction with work-life balance • Desire for new/ challenging tasks and topics
F: "I Lack Career Development Opportunities"	• Opportunity to work on challenging tasks • Recommendation from friend/ colleague • Size and location of company • Career advancement	• Average relationship with coworkers • Very poor relationship with supervisor	• Lack of career opportunities • Poor working relationship with supervisor • Dissatisfaction with general working environment • Insufficient non-monetary recognition • Lack of personal development and poor social interactions
G: "I Just Don't Fit Here Anymore"	• Opportunity to work on challenging tasks • Size and location of company • Company culture • Career advancement	• Average relationship with coworkers • Very poor relationship with supervisor • Average relationship with coworkers and supervisor	• Various reasons

within the organization. Employee relationships are significant in IT because most work is conducted in teams. We believe that career goals and employee relationships are important determinants of job satisfaction, which is an important driver of turnover. The classification is also based on the reasons given for leaving the organization.

The seven types are summarized in Table 1, which for each type lists the motivations for originally joining, the state of the relationships between the leaver and his or her coworkers and supervisor, and the reasons for leaving.

Below, we suggest retention strategies that could have been applied to each of these types of leavers and a process for implementing the retention actions. These actions are intended to support IT managers in the retention of IT professionals and, as a result, reduce—or even prevent—IT employee turnover.

Type A IT Leavers: "I Have No Real Stock Here"

Summary. This type of IT leaver joined the organization because of a recommendation from a friend or previous colleague. The relationship with coworkers was average, but slightly poorer with the supervisor. This type of leaver gave four main reasons for moving on: insufficient non-monetary recognition for achievements/contributions, a lack of career opportunities, dissatisfaction with the general working environment and a job offer from another company. On average, this type of IT employee stays in their job for nearly 2,000 days (Table 2)—about a year longer than the other types.

Indicators for Type A Leavers. The main indicator that this type of IT employee may be considering leaving is that, although they are not dissatisfied, they are not particularly happy with their work situation. Another indicator is that they have worked for the company for quite a while. A possible third indicator is that they have a slightly poorer relationship with their supervisor than their peers.

Type A leavers feel they have not received appropriate or sufficient recognition for work performed. They do not foresee future career opportunities with their current employer, possibly as a result of the poorer relationship with the supervisor. As the overall situation of Type A leavers is not particularly bad, they often are not actively looking to leave. Rather, external events, such as a job offer, finally convince them to hand in their notice to leave. Turnover among Type A IT employees is difficult to anticipate because they do not communicate their dissatisfaction. From an IT manager's perspective, there is little warning until an apparently minor incident convinces them to leave.

Retention Actions. 60% of Type A leavers, compared to 53% of the six other types, stated that they could have been persuaded to stay: 45% of these said they would have stayed if they had received a pay raise, 30% would have stayed if they had been offered new career opportunities/challenges, and 20% would have reversed the decision to leave if they had been assigned to a different supervisor.

The best retention action for Type A IT employees is to initiate informal conversations with the aim of building trust and providing them with the feeling that the IT manager cares about them.

"You have to regularly talk with [Type A IT employees], but in an informal way. … The conversation should be about their job satisfaction, career possibilities and about areas in which they can improve; not too direct but in an honest way." IT Manager

Having identified a person as a Type A IT employee, it might be advisable not to expose her or him to an external event such as attending a conference. Instead, the IT manager should carefully examine the employee's preferences and provide transparent career options.

Table 2: Characteristics of Type A IT Leavers

Average tenure (days)	1,990
Previously considered leaving	20%
Turnover was preventable	60%
Talked first to supervisor about intention to leave	40%
Reasons for joining the organization	Recommendation from friend/colleague (85%)
Reasons for leaving	Insufficient non-monetary recognition (65%)
	Lack of career opportunities (55%)
	Dissatisfaction with general work environment (25%)
	External job offer (response to open question)

Type B IT Leavers: "This is the Wrong Job for Me"

Summary. The primary original motivation for Type B leavers to join the company was that they wanted to work on challenging tasks. In general, Type B employees have a normal relationship with their coworkers and get along well with their supervisor. The main reasons given by this type of IT employee for leaving are a poor fit with the assigned task, dissatisfaction with the general working environment and a lack of career opportunities (see Table 3).

Indicators for Type B Leavers. Type B IT employees originally joined the company because of an opportunity to tackle challenging tasks but then become dissatisfied with these tasks and the general working environment. This causes an imbalance between personal expectations and the reality of the job. Despite their dissatisfaction with their current work, Type Bs have good relationships, especially with their supervisor. This good relationship opens the door for IT managers to talk openly with Type B employees about current tasks and their goals within the organization. The shorter average tenure of this type of leaver (960 days) suggests that they realized early on that either the job or the task did not match their expectations.

Retention Actions. At 81%, the proportion of Type B leavers who stated that they could have been prevented from leaving is larger than that of the other types (about 53%). Because this type of IT employee has good relationships with colleagues, their dissatisfaction with the general working environment is mainly related to dissatisfaction with the assigned tasks and a lack of career opportunities. This implies that turnover among Type B IT employees is primarily related to the way they are managed and could have been prevented. One of our interviewees said that his company had identified the link between incorrectly assigned IT employees and increased turnover. In response, new job openings are now advertised internally as well as externally.

"We now have the possibility of internal application. Job offers are promoted internally and employees may apply for those jobs. … We expect that our executives don't cling to their subordinates—those who want to work somewhere else … leave the company. Ideally it's better if they stay in the company but work on a different job." IT Manager

Other important retention actions for Type B IT employees is providing career development opportunities and finding more suitable tasks. However, finding the right or new tasks immediately might not be possible. The IT manager should reassure the employee that her or his wishes have been noted and assignment to a new task will be accomplished as soon as possible.

Type C IT Leavers: "The Job Does Not Fit with My Spouse's or Partner's Needs"

Summary. Type C IT employees often join the organization because of a recommendation from a friend or because of the organization's size and location. They have a very good relationship

Table 3: Characteristics of Type B IT Leavers

Average tenure (days)	960
Previously considered leaving	31%
Turnover was preventable	81%
Talked first to supervisor about intention to leave	56%
Reasons for joining the organization	Opportunity to work on challenging tasks (62.5%)
	Size and location of company (25%)
Reasons for leaving	Dissatisfaction with general working environment (93.8%)
	Lack of career opportunities (31.2%)
	Poor fit between employee and assigned task (response to open question)

with colleagues and get along well with their supervisor. Together with Type E IT Employees ("I Need Something New"), Type Cs have the best relationships within the organization of all the seven types. Their reasons for leaving are to do with personal/private issues and because of an unsatisfactory work-life balance. For example, their job may involve too much travel, their commute is too long or their partner lives in another city. This type of IT leaver mentioned a variety of private/personal triggers for leaving, some of which related to the needs of the spouse or partner (see Table 4). However, none of these triggers can be controlled or changed by the company.

Indicators for Type C Leavers. Because the triggers for leaving are based on the employee's private life, it may not be easy for IT managers to identify potential Type C IT leavers. However, conversations about their private lives might help managers to identify Type Cs. In general, indicators for Type C IT leavers are changes or events in their private lives such as getting married or becoming a parent.

The proportion of Type C leavers who had previously considered leaving is just 16%, the lowest of all seven types. Type C IT employees seem to be loyal to their company and satisfied with their current work situation.

Retention Actions. The majority of Type C leavers (73%) stated that they could not have been prevented from leaving the company. Turnover caused by private issues is very difficult to prevent.

"... you can say what you want [to Type C employees]—it doesn't change a thing. Even if you manage to change his mind, the urge will remain, and sooner or later he will eventually leave." IT Manager

Possible retention actions might be to create special working arrangements that would improve the employee's work-life balance or to offer a job at another of the organization's locations. However, these actions would only be effective if they addressed the private trigger.

"If [an employee comes to me and says] 'My partner has received a great job offer somewhere else, and therefore I am leaving,' then I think that the company can do something. For example, [it could] offer some kind of dual–career service, which aims to support dual-career couples." IT Manager

Personalized retention actions require substantial effort on the part of the IT manager and perhaps even by company administration but can lead to increased loyalty in the longer term. IT managers might therefore consider initiating them only for employees with high value to the company or department. If it is not possible to prevent a Type C IT employee from leaving, it is important to communicate that he or she is welcome to return should the personal situation change.

Type D IT Leavers: "I Do Not Like It Here"

Summary. Type D IT employees originally joined the organization because of a recommendation from a friend or colleague,

Table 4: Characteristics of Type C IT Leavers

Average tenure (days)	1,600
Previously considered leaving	16%
Turnover was preventable	27%
Talked first to supervisor about intention to leave	65%
Reasons for joining the organization	Recommendation from friend/colleague (84%)
	Size and location of company (29.7%)
Reasons for leaving	Dissatisfaction with work-life balance (27%)
	Dissatisfaction with general work environment (24.3%)
	Different personal triggers, most of which are related to private life
	Relocation is a frequently reported trigger (response to open question)

Table 5: Characteristics of Type D IT Leavers

Average tenure (days)	1,690
Previously considered leaving	50%
Turnover was preventable	72%
Talked first to supervisor about intention to leave	44%
Reasons for joining the organization	Recommendation from friend/colleague (61.1%)
	Company culture (33.3%)
	Size and location of the employer (27.8%)
Reasons for leaving	Supervisor (55.6%)
	Insufficient non-monetary recognition (33.3%)
	Dissatisfaction with general working climate (27.8%)
	Lack of career opportunities (22.2%)
	Dissatisfaction with work-life balance (22.2%)

or because of the company culture, size or location. Despite initial enthusiasm, Type Ds seem unhappy with their current situation. Their relationships with their supervisor and with their coworkers are poor. In comparison to the other six types, poor social relationships seem to be the dominant factor for their dissatisfaction. In general, Type D IT leavers mention a broad variety of reasons for leaving, including their supervisor, a lack of non-monetary recognition, the general working climate, lack of career opportunities and work-life balance (see Table 5).

Indicators for Type D Leavers. Because Type D IT employees have poor relationships within the company, it might not be easy to identify potential leavers of this type. The main indicator for Type D IT leavers is that they express dissatisfaction with nearly everything.

Retention Actions. Although unhappiness with the work situation might be difficult to rectify, 72% of Type D leavers stated that they could have been prevented from leaving. However, it is hard to see how an IT manager could convince a Type D employee to stay with the company. In fact, the best action might be to let the individual leave. Unhappiness with the current job and company might be a source of negativity and spread within the team.

"A dissatisfied employee can be the infamous 'rotten apple.' When you mix a rotten apple with five healthy ones, two or three others are infected. You really have to be careful." IT Manager

However, if the employee is a valuable resource, and it makes sense to initiate efforts to retain her or him, a change of department might be the most promising approach. This could offer the employee an opportunity to start over with new co-workers, a new supervisor and possibly new projects.

Type E IT Leavers: "I Need Something New"

Summary. With an average tenure of 2,210 days, Type E IT employees stay with the company the longest. They originally joined the organization because of a recommendation, the prospect of challenging tasks, the company culture or the opportunity to advance their careers. Type Es have very good relationships with coworkers and their supervisor. The main reasons they give for leaving are the lack of career opportunities and dissatisfaction with work-life balance. Other triggers for leaving mentioned by Type Es are related to their desire to work on new tasks and new projects (see Table 6).

Indicators for Type E Leavers. Many Type E characteristics are similar to those for Type C ("The Job Does Not Fit with my Spouse's or Partner's Needs"). However, the main triggers for a Type C IT employee leaving are to do with personal/private issues, whereas the main

Table 6: Characteristics of Type E IT Leavers

Average tenure (days)	2,210
Previously considered leaving	35%
Turnover was preventable	52%
Talked first to supervisor about intention to leave	70%
Reasons for joining the organization	Recommendation from friend/colleague (87%)
	Opportunity to work on challenging tasks (39.1%)
	Company culture (21.7%)
	Career advancement (21.75%)
Reasons for leaving	Lack of career opportunities (30.4%)
	Work-life balance (26.1%)
	Desire to work on different tasks and projects (response to open question)

reasons for Type E employees leaving are related to their career and the job. Another difference between these two types is that 52% of Type E leavers stated that their departure could have been prevented, whereas only 16% of Type C leavers could have been persuaded to stay at the organization.

Retention Actions. The average tenure of Type E IT employees is nearly seven years, during which, they may well have been performing similar tasks and may therefore have become bored with their job. IT managers can prevent Type E employees from leaving by offering them new projects and new career opportunities. However, these retention actions will be successful only if the individual plans to stay in the IT profession and if the company can offer topic-related training. Retaining an IT employee seeking a change of career may be difficult. The best option might be for the IT manager to assure the individual that she or he is welcome to return if things do not work out.

"There are employees who say: 'Everything is OK here, but now I need to see something new.' And that's alright. The only thing you can do is to bid them farewell and say 'If you get tired after three years, you are welcome to come back to us. … The doors are open.'" IT Manager

Type F IT Leavers: "I Need Something New"

Summary. Type F leavers originally joined the organization because they wanted to work on challenging tasks, a friend or colleague recommended the organization, they liked the location of the company, or they were looking for career advancement. All aspects of Type F's relationships within the organization are rated lower than average. The relationship between Type F employees and the supervisor is particularly poor. The most frequently mentioned reason for leaving is a lack of career opportunities, followed by the supervisor, the general working environment and a lack of non-monetary recognition. Personal development and poor social interactions were frequently mentioned in the responses to open questions as reasons for leaving (see Table 7).

Indicators for Type F Leavers. The main characteristic of Type F IT employees is the poor relationship with the supervisor and their demand for career opportunities. Type Fs do not feel valued and might feel blocked in their career by their current work situation. They joined the organization hoping to work on challenging tasks, but feel they cannot achieve their goals.

Retention Actions. The majority of Type F leavers (72%) stated that they could have been prevented from leaving. To retain a Type F employee, IT managers should first evaluate whether the perceived block in career advancement is real or if the employee has a false impression. Assessing the validity of this perception might reveal that the employee is not of value to the department or company, and the best action might be to let the employee leave.

Table 7: Characteristics of Type F IT Leavers

Average tenure (days)	1,580
Previously considered leaving	20%
Turnover was preventable	72%
Talked first to supervisor about intention to leave	56%
Reasons for joining the organization	Opportunity to work on challenging tasks (72%)
	Recommendation from friend/colleague (44%)
	Size and location of the company (40%)
	Career advancement (36%)
Reasons for leaving	Lack of career opportunities (52%)
	Supervisor (32%)
	Dissatisfaction with general working environment (32%)
	Insufficient non-monetary recognition (24%)
	Personal development and poor social interactions (responses to open question)

Offering new career opportunities, a change in supervisor or the chance to apply for internal positions might aid in retaining Type F IT employees.

"We had this very competent employee who aimed at becoming head of department. However, we had chosen someone external for this position. He was very disappointed, and after a year, suddenly, he joined one of our main customers. … [His departure] was our fault. We should have given him another career perspective after the [new] head of department blocked his way." IT Manager

Several of the IT managers we interviewed reported that their organizations had introduced the "strengthening strengths" approach, which aims to help employees identify their strengths and plan their career progress accordingly. This approach might be an effective action for retaining Type F IT employees.

Type G IT Leavers: "I Just Don't Fit Here Anymore"

Summary. Type G leavers mentioned several different reasons for originally joining the organization. The most frequent were challenging tasks, the size and location of the company and company culture. Type Gs have an average relationship with their coworkers and their supervisor. They also mentioned several different reasons for leaving, the most frequent being dissatisfaction with the available career opportunities and inadequate work-life balance (see Table 8).

Indicators for Type G Leavers. Type G leavers mentioned a broad variety of motivations for originally joining and reasons for leaving. Their relationships with others in the organization were average. While no single reason for leaving stands out, it seems that the combination of several different factors contributes to the decision to leave. If a certain threshold of negative aspects is reached, Type Gs suddenly decide to leave, making it difficult to identify specific reasons for their decision.

Retention Actions. Half of Type G leavers stated that their departure could have been prevented. Given the broad variety of joining motivations and leaving reasons, no clear, single action could have retained this type of IT employee. Thus, it is difficult to select one right retention action for Type Gs—financial compensation may be the only action that could retain a Type G IT employee.

"Honestly, the best retention strategy for [Type G IT employees] is money. They have various different reasons [for leaving]. … Financial motivation works the best in such situations." IT Manager

Table 8: Characteristics of Type G IT Leavers

Average tenure (days)	1,570
Previously considered leaving	25%
Turnover was preventable	50%
Talked first to supervisor about intention to leave	58%
Reasons for joining the organization	Opportunity to work on challenging tasks (55.6%)
	Size and location of company (49.3%)
	Company culture (31.2%)
	Career advancement (22.9%)
Reasons for leaving	Lack of career opportunities (34.7%)
	Work-life balance (25.7%)
	A broad variety of reasons concerned with private life, salary and dissatisfaction with the current project and job (responses to open question)

Addressing the Challenges of Retaining IT Professionals

Table 9 depicts how effective the five retention actions are for each of the seven types of IT employee. Each cell shows if the action is definitely helpful (a filled circle), might be helpful (a half-filled circle) or probably not helpful (an empty circle). We strongly recommend definitely helpful actions when trying to retain a particular type of IT employee. Might be helpful actions could be considered, but the probability of success is lower than for those actions identified as definitely helpful. Probably not helpful actions have a low probability of success. These actions can still be considered, but other retention actions should be applied first.

The table shows that it is unlikely that one overall retention action will be successful for all IT professionals because of their diverse reasons for joining the organization, their diverse ability to get along with others and their diverse attitudes to their job situation.

Customizing the Retention Process Based on IT Employee Type and Proposed Retention Actions

Choosing the most effective retention actions for each type of IT employee is part of the larger retention process shown in Figure 1. The process starts when the IT manager senses weak signals that an employee is considering leaving. These signals can be related to private or professional life and may include becoming a parent, updating a résumé on professional network sites like LinkedIn or becoming less motivated at work. Some employees actively look for an opportunity to talk with their supervisor to express their dissatisfaction. According to the IT managers we interviewed, most of the time it is possible to predict quite well whether an employee is considering leaving.

After receiving weak signals that an IT employee is considering leaving, the manager assigns that individual to one of the seven types of IT employee. The decision on type is based on various indicators, such as observing the employee during daily work, feedback from co-workers, informal conversations or, for example, reaction to being asked to work overtime in critical project phases. Table 10 lists the personal characteristics that determine employee type.

After identifying the individual's employee type, the IT manager needs to decide if that employee should be retained or let go. Usually, managers try to retain IT employees because of high demand in the job market, but there are exceptions—for example, when the individual does not fit the organization.

It may not make sense to try and retain some types of IT employees—Type D ("I Do Not Like It Here"), for example, or Type F ("I Lack Career

Table 9: Retention Actions for Different Types of IT Employees

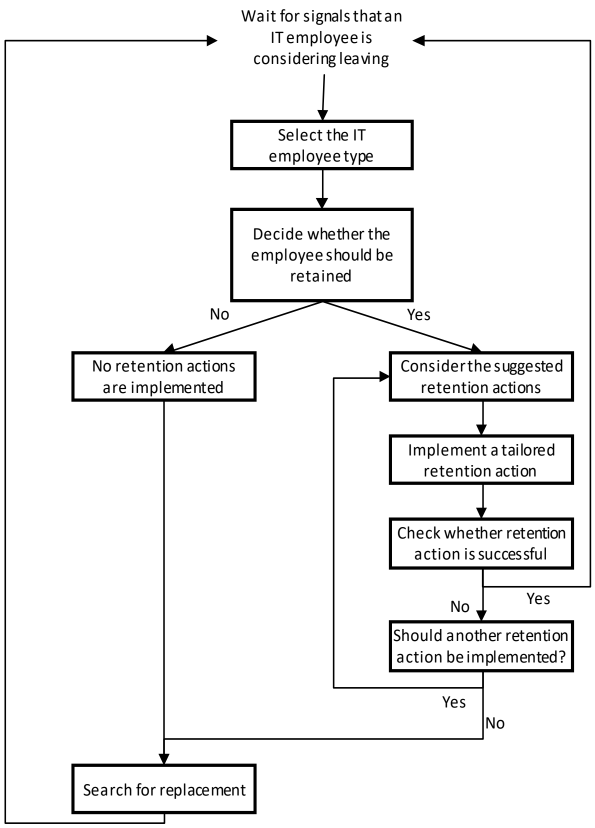
Retention Action/ Employee Type	Compensation	Working Arrangements	Career Development	Change of Department	Varying Work Tasks
A: "I Have No Real Stock Here"	●	○	◒	◒	○
B: "This is the Wrong Job for Me"	○	○	●	○	●
C: "The Job Does Not Fit with my Spouse or Partner's Needs"	○	◒	○	○	○
D: "I Do Not Like It Here"	○	○	◒	●	○
E: "I Need Something New"	○	○	●	◒	●
F: "I Lack Career Development Opportunities"	◒	○	●	●	○
G: "I Just Don't Fit Here Anymore"	●	○	◒	○	○

● = Definitely helpful ◒ = Might be helpful ○ = Probably not helpful

Table 10: Characteristics Identifying Employee Type

Employee Type	Characteristics Identifying the Respective Employee Type
A: "I Have No Real Stock Here"	• Does not take ownership of problems • Seeks security in career perspectives • Not actively job seeking
B: "This is the Wrong Job for Me"	• Requests changes in job responsibilities • Seeks challenging tasks • Fit in social environment
C: "The Job Does Not Fit with my Spouse's or Partner's Needs"	• Positive attitude to overtime as long as it fits private life • Strong personality • Changes in personal life
D: "I Do Not Like It Here"	• Many complaints about working environment • Poor relationship with supervisor • Actively thinks about leaving
E: "I Need Something New"	• Long time in same position • Positive attitude to current job • Seeks new tasks
F: "I Lack Career Development Opportunities"	• Missed promotion • Dissatisfied with working environment • Poor relationship with supervisor
G: "I Just Don't Fit Here Anymore"	• Various reasons for dissatisfaction • Does not respond to single retention actions

Figure 1: Choosing Retention Actions Is Part of the Retention Process



Development Opportunities”). These types of IT employees may have poor relationships with colleagues and supervisors and retaining them may have a harmful effect on the remainder of the team. Their dissatisfaction could hinder organizational processes and adversely affect the working climate within the whole department. On the other hand, Type B (“This is the Wrong Job for Me“) IT employees get along well with their coworkers and supervisor but are unhappy with their assigned tasks. They might be worth keeping by assigning them to other tasks. The costs of any retention actions should also be taken into account when deciding whether to make the effort to retain an individual.

If the IT manager decides that the IT professional should not be retained, no retention actions are implemented, and the search for a replacement begins.

Where the decision is to try and retain an IT employee, appropriate actions for the employee type, as shown in Table 9, are chosen and tailored to the specific situation. After implementing one of the retention actions, the IT manager assesses the effect of the action. If the outcome was not positive (i.e., the employee still plans to leave), then another retention action should be implemented. If all the retention actions do not stop the employee from leaving, the only recourse is to hire a replacement.

Lessons Learned for Retaining IT Professionals

Experienced IT managers may already have their own actions for identifying employees considering leaving and for reducing IT employee turnover. However, our classification of IT employee types, the description of appropriate retention actions for each type and the retention process described above form the basis of a strategy for reducing the turnover rate of IT professionals that will be useful for less experienced managers. The elements of this strategy could, for example, be incorporated into managerial training programs.

“Our company has a special training program for IT managers. This retention framework could be a useful part of this training.” IT Manager

As well as developing the framework for a strategy for retaining IT professionals, our analysis of the exit questionnaires completed by employees of the German IT services provider and our interviews with IT managers at that firm revealed six lessons that will help managers to retain IT professionals.

Lesson 1: Know Your Employees

The relationship between IT manager and IT employee is very important. The manager will be better placed to identify those employees who might be considering leaving if he or she knows something about the employees, such as their motivations for originally joining the organization, their career goals and perhaps a bit about their private lives. Continually assessing the probability of an employee leaving may help the IT manager to intervene to prevent that happening.

To identify the most appropriate retention action for each employee type and tailor it to the specific situation, the manager has to know enough about the employee to assign her or him to an employee type. This requires more than the formal yearly performance review. Informal chats while having coffee or leaving the building together can provide opportunities for the manager to establish a trusting relationship with the employee or simply learn more about her or his professional and personal life. Informal chats, however, may be difficult to hold if the IT manager and the employee are not colocated. An IT manager we interviewed who manages a team of consultants working at a customer's site told us that he has established monthly audio conferences so he and the consultants can talk about things outside of daily business.

Lesson 2: Optimize Career Opportunities and the Internal Job Market

Our study shows that career development is an important retention action that is effective especially for IT employee Types B ("This is the Wrong Job for Me"), E ("I Need Something New") and F ("I Lack Career Development Opportunities"). Career development could also be appropriate for Types A ("I Have No Real Stock Here"), D ("I Do Not Like It Here") and G ("I Just Don't Fit Here Anymore"). IT employee Types B and E can be retained by assigning them to new and more challenging tasks. Developing a structured career plan specifically tailored to each individual IT employee that focuses on their individual strengths can also help to reduce turnover.

An internal job market that allows employees to apply for a position within the organization without the permission of their supervisor can provide IT professionals with opportunities both for career advancement and for working on new and diverse tasks. Experienced IT managers see internal job markets as an effective way of reducing turnover. Although the IT department might lose a valued staff member, it is probably better to lose an employee internally than to a competitor. Whether formal or informal, internal job markets should be designed to retain talent within the company.

Lesson 3: Align Retention Actions to the Organizational Context

IT managers have to consider the current context of the organization when they select retention actions. The size and structure of the organization determine whether certain retention actions are possible. For instance, Type E IT leavers ("I Need Something New") mentioned the desire to work abroad as a major reason for leaving. Larger organizations with offices around the globe can offer positions in another country; smaller nationally based businesses can't. Another factor to consider when selecting retention actions is the current workload. For instance, giving an employee a new task or assigning him or her to a new department may not be possible if the employee is key to the success of a project. Assuring the employee that he or she will be reassigned to a new department as soon as the project is completed is an honest and open solution that demonstrates the manager's willingness to act in the interest of the employee. Providing training for the employee in preparation for the new task makes the manager's intentions more credible.

Lesson 4: Keep the Door Open

Some types of IT employee have good relationships within the organization and enjoy working for it. This is especially true for Types B ("This is the Wrong Job for Me"), C ("The Job Does Not Fit with my Spouse's or Partner's Needs") and E ("I Need Something New"). These types generally leave because they dislike their assigned tasks or for personal reasons. IT managers should leave open the option of rehiring these types of employee should their situation change in the future or should they change their mind. IT professionals who leave an organization for personal reasons have a positive attitude to the organization, and there is a high probability of them returning in the future. Maintaining personal contact and establishing alumni networks have been shown to be effective methods for re-employing former staff members.

Lesson 5: Conduct Post-entry Interviews

Post-entry interviews help to establish a personal rapport with a new employee and may help to identify at an early stage if he or she is at risk of leaving in the future. Conducting this type of interview at the six-month probation review may be too late to identify factors contributing to unhappiness. Early on, managers should

Table 11: Applying the Lessons Learned to Overcome IT Employee Retention Challenges

Retainment Challenges	Lessons Learned for Retaining IT Professionals
Evaluate which retention strategies are effective	Know your employees
IT employees like to work on diverse tasks and desire career advancement	Optimize career opportunities; establish an internal job market
Retention actions have different requirements and consequences	Align the retention actions with the organizational context
Some employees that have left might consider re-joining the organization in the future	Keep the door open for re-employment
Get to know new employees early on, and be attuned to recognizing early on those at risk of leaving in the future	Conduct post-entry interviews
Retention actions differ in their short- and long-term effects	Financial compensation leads to short-term retention, whereas working arrangements, career development, department change and assignment to new tasks or projects lead to retention in the mid- and longer-term

understand the motivations of their employees for joining the organization and their career goals, so they can guide them in the right direction. Post-entry interviewees also give employees the feeling that the organization cares about them, their goals and their job satisfaction.

Lesson 6: Financial Compensation Leads to Short-term Retention

The retention actions described in this article have different short- and long-term effects. Whereas working arrangements, career development, department change and assignment to new tasks or projects lead to the retention of an IT employee in the mid- and longer-term, improved financial compensation generally only has a short-term effect because it does not adequately address the reason for employee dissatisfaction. While compensation is a form of appreciation, its impact dwindles over time.

IT managers should consider a combination of retention actions with different timescales for their effects. Financial compensation can be an action to buy time, which then allows for the implementation of another retention action with a longer-term effect. IT professionals, particularly younger ones, are more focused on career opportunities, interesting tasks and their private life than on financial compensation. Their job has to be diverse, appealing and fit their image of their life. IT managers have to consider a broader range of retention actions in the future to convince an employee to stay. Financial compensation by itself is an insufficient retention action.

Table 11 summarizes how each of these six lessons helps IT managers to overcome the challenges of retaining IT professionals.

Concluding Comments

Turnover of IT professionals is problematic for IT organizations, and efforts should be taken to reduce or prevent it. IT managers should match retention actions with reasons for leaving, but because these reasons differ greatly according to the type of IT professional, it can be difficult to choose the most appropriate retention actions. We have proposed a strategy for retaining IT professionals, which classifies IT leavers (and employees) into seven types. We have provided advice on how IT managers can choose the most effective retention actions for each of these types. We have also identified six lessons that IT managers can apply as they seek to reduce turnover among their employees. Adopting our proposed strategy and implementing one or all of the lessons learned will provide a starting point for IT managers to reduce turnover rates among IT professionals.

Appendix: Research Method

We cooperated with a large German IT service provider, which wishes to remain anonymous. This vendor has a solid reputation in the industry and is among the 10 largest IT service providers in Germany. During the last decade, it has pursued a constant growth strategy. It generates most of its revenue through consulting projects, software development and large application hosting projects for clients from various industries, including insurance, banking and automotive.

We followed a two-stage process for developing the classification of seven types of IT leavers and identifying retention strategies. First, the IT leaver types were derived from an analysis of the exit questionnaires completed between 2008 and 2013 by 283 employees of the German services provider just before they left. To obtain a comprehensive picture of the firm's former employees, we asked about their original motivations for joining, their relationships within the organization, retention actions that would have worked and their reasons for leaving. The obtained data from the questionnaires was processed by a clustering algorithm, which identified seven different clusters (i.e., types of IT leavers). These clusters were improved during subsequent interviews with IT managers at the service provider.

Second, we analyzed the triggers for leaving reported by these IT leavers and, particularly, any possible retention actions they mentioned. The focus of this analysis was on deriving retention strategies that could be applied by IT managers. These strategies were further developed and refined during subsequent interviews with eight IT managers at the services provider.

In addition to identifying the seven types of IT leavers and the corresponding retention actions, we developed a process for implementing the actions. This model was improved and revised during interviews with the IT managers.

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Appendix F – Publication P5

The Explanatory Power of the Constructs of Transaction Cost Economics Theory

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ABSTRACT

This Paper analyses the explanatory power of the constructs of transaction cost economics theory (environmental uncertainty, behavioral uncertainty, asset specificity and transaction frequency) in order to determine possible constructs for an endogenous theory of ITO. To analyze this, we employ a large project data set from a German IT outsourcing vendor. We find that only environmental uncertainty and transaction frequency have a high explanatory power and therefore should be considered for an endogenous theory of ITO. Behavioral uncertainty and asset specificity are only of minor relevance. The research is limited by the fact that we employed a data set from only one vendor. We contribute to theory by suggesting possible constructs for an endogenous theory of ITO and to practice by showing that the danger of opportunistic behavior is low. This paper contributes to the ongoing discussion on the applicability of transaction cost economics theory.

Keywords

Transaction Cost Economics, IT Outsourcing, Governance Mechanisms, Choice of Contract Type

INTRODUCTION

The global information technology outsourcing (ITO) market has reached nearly $400bn in 2015 (Statista 2016). ITO is defined as the assignment of an IT task to a vendor, who charges a fee for conducting the service (Apte, Sobol, Hanaoka, Shimada, Saarinen, Salmela and Vepsalainen 1997; Lacity and Hirschheim 1993; Loh and Venkatraman 1992). These IT tasks can be various and range from “simple data entry to software development and maintenance, data center operations and full system integration” (Apte et al. 1997).

Transaction Cost Economics is one of the leading frameworks for analyzing the phenomenon of ITO (Dibbern, Goles, Hirschheim and Jayatilaka 2004; Klein 2002). It has also been frequently used for analyzing the chosen governance mechanism or for explaining the contract choice for ITO projects (e.g. Kalnins and Mayer (2004), Gefen, Wyss and Lichtenstein (2008) and Gopal, Sivaramakrishnan, Krishnan and Mukhopadhyay (2003)).

Recent studies about the role of TCE in ITO show inconsistent results (Karimi-Alaghehband, Rivard, Wu and Goyette 2011; Lacity, Willcocks and Khan 2011; Schermann, Dongus, Yetton and Krcmar 2016). Schermann et al. (2016) conducted a meta-analysis about the influence of uncertainty, which is a central construct of TCE, on contract choice. Although TCE has been used for explaining the influence of various kinds of uncertainty, they found that the operationalization of uncertainty has a significant influence on the predictability of TCE. This supports the call by Karimi-Alaghehband et al. (2011) for a more rigorous application of TCE in ITO research. They conducted a literature review on the use of TCE in ITO studies and found that only a few studies use all constructs of the theory. However, Schermann et al. (2016) also found that the predictability of TCE significantly decreased after the year 1999. This supports the call by Lacity et al. (2011) to develop a new analytical framework for the ITO domain. In their literature review on the usage of TCE in ITO, they explain the found mixed results with the limited explanatory power of TCE.

However, there is limited empirical evidence that questions the application of TCO in ITO. Schermann et al. (2016) do not employ environmental and behavioral uncertainty, the two categories of uncertainty, mentioned by Williamson (1985). They rather focus on the construct task uncertainty. Analyzing the explanatory power of the original constructs instead of derived ones gives a better picture whether the original theory is applicable. Furthermore, other TCE constructs beyond uncertainty, such as asset specificity and transaction frequency have not been examined.

Other issues are related to meta-analyses. First, they are based on subjective coding of heterogeneous samples, differing in project and company size, time frame, and variable operationalization. Second, meta-analyses and literature analyses are subject to the file drawer problem, which might be especially an issue when examining the explanatory power of a theory (Borenstein, Hedges, Higgins and Rothstein 2009). It argues that studies with significant results tend to get published more often. Therefore, meta-analyses and literature analyses rely on a biased data basis.

Lacity et al. (2011) call for the development of a new analytical framework. However, it remains unclear which constructs should be part of this framework. TCE consists of different individual constructs, that could be part of a newly developed framework. However, the relevance of the individual constructs remains unclear. In order to address this research gap, we formulate the following research question to address the previously discussed situation: *How well do the individual TCE constructs explain the governance choice in ITO transactions?*

To address this research question, we conducted an empirical study with a unique quantitative dataset from a German ITO vendor, called ALPHA. The dataset covers all projects conducted by ALPHA between 1995 and April 2014. The initial dataset contains more than 36,000 projects for about 2,000 different clients.

We find that environmental uncertainty is the only important TCE construct that has a huge explanatory power. We conclude that a new analytical framework should contain environmental uncertainty as a central construct.

The remaining sections of this paper are structured as follows. First, we present the theoretical background of the paper and develop our hypotheses. Then, we explain our research method including the employed variables. After that the results of the data analysis are shown. Finally, the paper ends with a discussion of the found results.

THEORETICAL BACKGROUND

The three central constructs of TCE are uncertainty, transaction frequency and asset specificity (Williamson 1985). Uncertainty can be further divided into environmental and behavioral uncertainty (Williamson 1985). Environmental uncertainty is related to uncertainty that stems from the lack of knowledge about the future state regarding the environment of the transaction (Susarla, Barua and Whinston 2009). Behavioral uncertainty deals with uncertainty that originates from the lack of knowledge regarding the actions of the in the transaction involved actors (Susarla et al. 2009).

Asset specificity is defined as the "degree to which the assets used to conduct an activity can be redeployed to alternative uses and by alternative users without sacrifice of productive value" (Williamson 1996). It can be divided into site specificity (geographical site of investment), physical asset specificity (Equipment and tools) and human asset specificity (knowledge and learning of employees) (Karimi-Alaghehband et al. 2011).

Transaction frequency focuses on the recurrence of activities that are needed for the transaction (Karimi-Alaghehband et al. 2011). Transactions can occur only occasionally, but also permanently.

The extent to which TCE has been employed varies. According to Carter and Hodgson (2006), only a few studies analyze all three constructs. This is as well criticized by Lacity and Khan (2016). According to Karimi-Alaghehband et al. (2011), although transaction frequency and asset specificity might be non-significant, they should be included in studies.

TCE is used for explaining two decisions made by the customer: whether to outsource or not, which is known as the make-or-by decision, and for choosing the mode of governance (Williamson 1991). In this paper, we focus on the second decision, namely on the chosen governance mechanism, which is predominantly determined by the type of contract.

The two prevalent types of ITO contracts are fix-price (FP) and time and material (TM) contracts (Gopal et al. 2003; Lichtenstein 2004). In FP contracts, the ITO vendor agrees to deliver a predefined result and is compensated with a certain fee (Ethiraj, Kale, Krishnan and Singh 2005). TM contracts are different because the billing is based on the agreed hourly rate and the working hours that the ITO vendor invested (Ethiraj et al. 2005).

The behavioral uncertainty component of TCE has been used to explain how the familiarity between the vendor and the client influences the contract choice. Increased familiarity decreases the danger of opportunistic behavior and therefore leads to increased TM contracting (Gefen et al. 2008; Kalnins and Mayer 2004).

Factors, such as project duration, project volume or requirements uncertainty of the project can also be assigned to the uncertainty component of TCE (Lacity and Khan 2016; Schermann et al. 2016). To be more precise, they are part of the environmental uncertainty. It has been found that higher project related uncertainty increases TM contracting (Gefen et al. 2008; Gopal et al. 2003; Kalnins and Mayer 2004; Susarla et al. 2009).

Asset specificity has been rarely used to explain the contract choice. Susarla et al. (2009) analyzed the influence of client specific investments by the vendor, but did not find a significant influence.

Recently, there have been studies that have found empirical inconsistencies between the prediction based on TCE and the observed results (Karimi-Alaghehband et al. 2011; Lacity et al. 2011). Karimi-Alaghehband et al. (2011) call for a more rigorous operationalization of TCE constructs and the usage of all constructs of the theory. Schermann et al. (2016) have shown that the magnitude of the relationship between uncertainty and the choice of governance mechanism is dependent on the operationalization of uncertainty. However, they have not used all TCE constructs, which has been criticized by Lacity and Khan (2016).

Opposed to the call of Karimi-Alaghehband et al. (2011) for a more rigorous operationalization of TCE constructs, Lacity et al. (2011) call for the development of an endogenous theory of ITO. They argue that the research on ITO has already matured to the point that an own theory makes sense. However, Lacity et al. (2011) only give broad propositions that could be part of the newly developed theory, but they argue for further research. They argue that a data driven theory development approach should be taken, as a theory based on data is more difficult to refute (Glaser and Strauss 2009).

As some of the TCE constructs have received empirical support (Karimi-Alaghehband et al. 2011; Lacity et al. 2011), we focus on the evaluation which of the TCE constructs could be part of a newly developed endogenous theory of ITO. Therefore, we analyze the explanatory power of environmental uncertainty, behavioral uncertainty, asset specificity and transaction frequency for choosing the governance mechanism.

IT projects are characterized by a high degree of uncertainty, such as the certainty of the requirements or changing technology (Nidumolu 1995; Schwartz and Zozaya-Gorostiza 2003). In general, the environmental uncertainty of transactions is very high in the ITO domain. The governance mechanism determines the flexibility of the transaction. For instance, it is quite easy to change requirements in a TM contract, but it is hardly possible under a FP contract (Gefen et al. 2008; Gopal et al. 2003). Environmental uncertainty has a high relevance in the ITO domain. Therefore, we formulate the following hypothesis:

H1: Environmental uncertainty has a high level of explanatory power

According to Williamson (1985), behavioral uncertainty is paramount to environmental uncertainty. It has been used by several ITO studies (e.g. Kalnins and Mayer (2004), Gopal et al. (2003) or Gefen et al. (2008)) for explaining the development of the ratio of TM and FP contracts over the customer lifetime. However, we argue that behavioral uncertainty is not of high relevance in the ITO domain. The ITO market is characterized with a high degree of competition (Manning, Lewin and Schuerch 2011). Acting opportunistically always has the danger that it comes out. This would destroy the reputation of the vendor and might even be fatal (Dibbern, Winkler and Heinzl 2008; Dongus, Yetton, Schermann and Krcmar 2014). ITO vendor extensively focus on building up a good reputation in their relationship with their customer, as this is a source for future business (Goles 2001; Levina and Ross 2003).

Therefore, it is quite unrealistic that there is a high danger of opportunistic behavior by the vendor. Because of this, the following second hypothesis is formulated:

H2: Behavioral uncertainty has a low level of explanatory power

According to Riordan and Williamson (1985), asset specificity has the greatest impact of all four TCE constructs. However, it remains unclear, whether this is also the case in the ITO domain. We argue that asset specificity has a low explanatory power in the ITO domain. Most of the asset specificity of an ITO vendor is related to human asset specificity. As IT employees are quite mobile and can easily work for other customers, the asset specificity in the ITO domain is not important. Furthermore, due to the high demand of ITO during the last years, it is easily possible to find a second best use for an IT employee. Therefore, we formulate the following third hypothesis:

H3: Asset specificity has a low level of explanatory power.

Transaction frequency has not received any empirical support (Karimi-Alaghehband et al. 2011; Lacity et al. 2011). A high frequency brings economies of scale regarding governance costs (Miranda and Kim 2006). For instance, FP contracts are more expensive to set up than TM contracts. These costs can be distributed over several contracts, if the transaction frequency is high. Due to the missing empirical support, we expect a low explanatory power of transaction frequency. Therefore, we formulate the following first hypothesis:

H4: Transaction frequency has a low level of explanatory power.

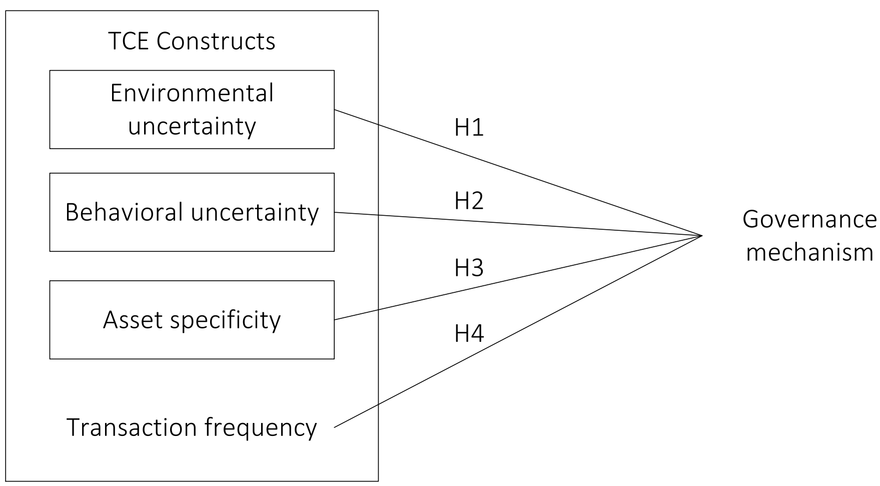

Figure 2: Research Model

RESEARCH METHOD

To address these hypotheses, we collected quantitative data from ALPHA, a large German IT service provider. ALPHA generates most of its revenue through consulting projects, software development and hosting for clients from various industries, such as insurance, banking and automotive. It has offices in more than 20 countries, but the majority of the business is conducted in Germany, Switzerland, Austria and the US. ALPHA has been founded in the early 1980s and therefore can be seen as a successful and established company.

The data have been extracted directly from the project controlling system of ALPHA who granted us access to all 36,413 projects conducted between January 1995 and April 2014. The information on the projects is of high quality because it was extracted from the project controlling system of ALPHA, which is also used for billing clients. Additionally, directly accessing quantitative data is not subject to recall bias, which could be a problem in case studies and surveys (Gefen et al. 2008).

We removed the years before 1997, in order to calibrate the dataset. The first project of a customer should really be the first one and not simply the start of the dataset. The number of short projects increases towards the end of the dataset as it includes only finished projects. To address this issue, the projects from 2013 and 2014 were removed to have a realistic composition of projects. Additionally, we filtered out internal projects and removed projects with incomplete data. The final dataset contains 22,701 projects for 1,736 different customers. Figure 2 shows the distribution of these projects over the years 1997 to 2012.

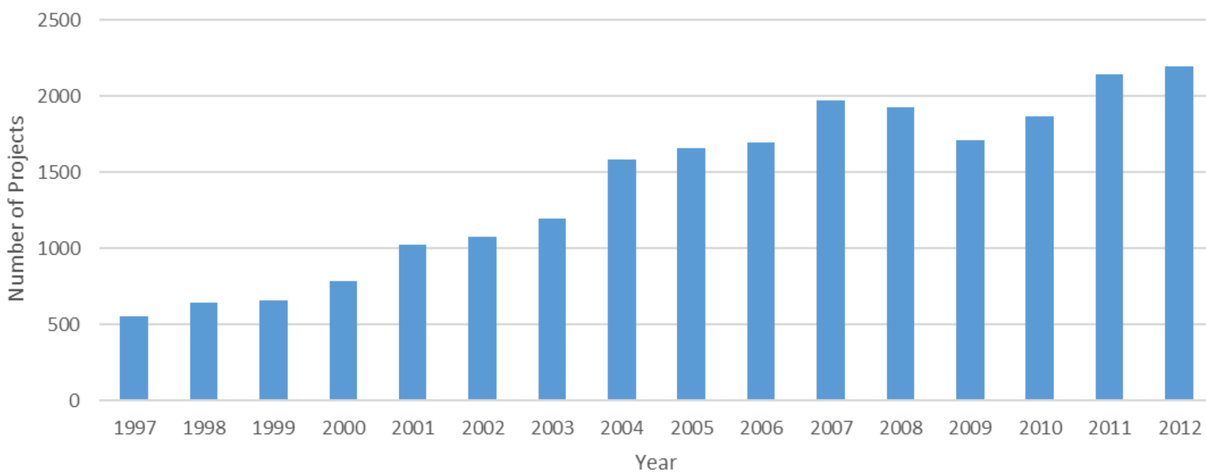

Figure 3: Distribution of Projects over the years

Variables

The dependent variable is the chosen *governance mechanism* of the transaction. This is mostly determined by the contract type of the project. The contract type has also been used by other TCE studies as a proxy for the chosen governance mechanism (Schermann et al. 2016). We focused on the two prevalent types of ITO contracts, namely FP and TM contracts (Gopal et al. 2003; Lichtenstein 2004). We coded FP as 1 and TM as 0. The type of ITO contract determines which party has to bear additional costs in case a realignment of the transaction is necessary (Hoermann, Hlavka, Schermann and Krcmar 2015).

The independent variables are environmental uncertainty, behavioral uncertainty, asset specificity and transaction frequency, that are described in the following paragraphs.

Environmental uncertainty: We used the volume of the project as a proxy for the uncertainty of the project which largely determines environmental uncertainty (Tiwana and Bush 2007). Larger projects tend to have a higher uncertainty and to be more complex (Banerjee and Duflo 2000; Gopal et al. 2003). As TM contracts allow more flexibility, the costs for realigning the transactions are lower. We employed the total hours worked for the project for approximating the project volume.

Behavioral uncertainty: The danger of opportunistic behavior is closely linked to the business familiarity between the customer and the vendor (Gefen et al. 2008). We employed the volume of prior contracts with the same customer as a proxy for customer familiarity. Another possibility is to measure it with the number of prior contracts (Gefen et al. 2008; Gopal et al. 2003). We have chosen the volume of prior contracts, because according to Gefen et al. (2008) it is better measured as the volume of prior contracts.

Asset specificity: We employed the average customer knowledge within the team, approximated by the average hours previously worked for the customer, as a proxy for asset specificity. Project team members gain knowledge about the customer during the conductance of a project. This knowledge is a form of asset that is most of the time can only be leveraged and is specific for a single customer. We only considered human assets, as site specificity and physical specific assets only play a minor in ITO (Aubert and Rivard 2016).

Transaction frequency: The number of projects in a timeframe of 180 days prior and after the project start with the same customer has been employed as a proxy for transaction frequency. Transaction frequency describes the activity of the customer in the market. As multi-vendor sourcing has gotten the dominant type of ITO in recent years (Dibbern et al. 2004), it can be assumed that a high number of transactions between ALPHA and a customer is a sign that this customer is an highly active customer in the market. Also future projects have been considered, because there is often a gap of several months between the first contacts between the vendor and the client, the signing of the contract and the actual project start. Furthermore, a vendor often can estimate the number of projects that will be conducted with the same customer in the following months quite well.

Data Analysis

As the dependent variable is dichotomous, we employed logistic regression. To analyze the explanatory power of the different TCE constructs several different regression models have been constructed, where each time a specific construct has been excluded. We use Nagelkerke's R2 for analyzing the explanatory power of the different constructed models (Nagelkerke 1991). We assume that a decrease in Nagelkerke's R2 by more than 10% is a sign of high explanatory power.

The following table shows some descriptive statistics of the employed subsets. Due to high skewness of project volume, customer familiarity, customer knowledge within team and transaction frequency, these variables are log-transformed (Hair, Black, Babin, Anderson and Tatham 2006).

Variable	Unit	Min	Mean	Median	Max	SD
Contract Type	0 = TM 1 = FP	0	0.4155324	0	1	0.4928244
Project Volume	Hours worked	0.25	1002.982	225.5	659172.5	6368.622
Customer familiarity	€ previous revenue	0	53,012,900	13,823,879	292,559,516	76,722,173
Customer Knowledge within Team	Hours	0	4,007.877	2,179.758	60,978.35	5,567.415
Transaction Frequency	#	1	38.29237	12	227	46.65994

Table 1. Descriptive Statistics (n=22,701)

The following tables show the correlation matrix of the employed variables.

	1)	2)	3)	4)	5)
1) Contract type	1.000				
2) log(Project Volume)	-0.130 ***	1.000			
3) log(Customer familiarity)	0.190 ***	0.168 ***	1.000		
4) log(Customer Knowledge within Team)	0.229 ***	0.145 ***	0.655 ***	1.000	
5) log(Transaction Frequency)	0.319 ***	0.022 ***	0.730 ***	0.649 ***	1.000

Table 2. Correlation Matrix (n=22,701)

RESULTS

Dependent variable: Contract type (0 = TM; 1 = FP)					
Variable	**Model 1 – Base model**	**Model 2 – H1 without environmental uncertainty**	**Model 3 – H2 without behavioral uncertainty**	**Model 4 – H3 without asset specificity**	**Model 5 – H4 without transaction frequency**

Intercept	-0.171653 ** (0.061289)	-0.906944 *** (0.049833)	-0.469704 *** (0.050874)	-0.211724 *** (0.061165)	-0.624506 *** (0.063302)
log(Project volume)	-0.181932 *** (0.008724)		-0.194560 *** (0.008604)	-0.173582 *** (0.008665)	-0.222016 *** (0.008478)
log(Customer familiarity)	-0.041345 *** (0.004957)	-0.059211 *** (0.004784)		-0.023297 *** (0.004640)	0.049687 *** (0.004324)
log(Customer Knowledge within Team)	0.063589 *** (0.005842)	0.052702 *** (0.005757)	0.047621 *** (0.005426)		0.115304 *** (0.005434)
log(Transaction Frequency)	0.399719 *** (0.013206)	0.439606 *** (0.012933)	0.337646 *** (0.010747)	0.444348 *** (0.012623)	
Nagelkerke's R2	0.1671814	0.1435973	0.163638	0.1608902	0.1160723
%-change of R2		14,1%	2,1%	3,8%	30,6%
Significance: *** = significant at the 0,1% level; **= significant at the 1% level; *= significant at the 5% level, †=significant at the 10% level					

Table 3. Results for constructed logistic regression models

The base model has a Nagelkerke's R2 of 16,7%. We find that all variables of the base model are highly significant.

For testing the first hypothesis, the project volume, which is a proxy for environmental uncertainty, has been excluded from the base model. We find that Nagelkerke's R2 drops by 14.1% to 14.4%. This is the second largest decrease and significantly higher than the third and fourth largest decrease. Therefore, hypothesis H1 is supported.

If customer familiarity, which is used as a proxy for behavioral uncertainty, is excluded, R2 only decreases by 2.1%, which is the smallest decrease of all constructs. As hypothesis H2 claims that behavioral uncertainty only has a low explanatory power, H2 is supported.

For testing hypothesis H3, we excluded asset specificity from the base model. We find that Nagelkerke's R2 only slightly drops by 3.8% from 16.7% to 16.1%. As this is the second smallest decrease and by far smaller than third smallest one, we can conclude that H3 is supported.

If transaction frequency is excluded from the base model, Nagelkerke's R2 decreases by 30.6% to 11.6%. This is the largest drop of all, but hypothesis H4 claimed that transaction frequency only has a low explanatory power, it is rejected.

DISCUSSION

Our results show that most of the explanatory power of TCE is based on only two constructs, namely environmental uncertainty and transaction frequency. The other two TCE constructs, behavioral uncertainty and asset specificity, do not seem to be that important. Therefore, environmental uncertainty and transaction frequency should be considered as possible new constructs for a new endogenous theory of ITO that should be developed after Lacity et al. (2011).

Before discussing the contribution of our results, limitations of our approach and data analysis are presented. First, the employed dataset comes from only one vendor, which is a threat to the generalizability of the results. On the other hand, data from the same vendor and multiple clients cancels out vendor specific effects and makes it possible to more thoroughly focus on the individual TCE constructs. Second, the chosen proxies for the TCE constructs might not be the perfect proxies. However, we employed proxies that have also been used by previous studies and have proven to be reliable. Furthermore, as we are dealing with data from an ITO service provider, we are limited to the available variables and cannot define our own variables.

We contribute to theory by showing that most of the explanatory power of TCE within the ITO domain is due to environmental uncertainty and transaction frequency. Therefore, these two constructs are candidates to be included in the newly developed endogenous theory of ITO after Lacity et al. (2011).

The high relevance of environmental uncertainty is opposed to Williamson (1985) who argues that behavioral uncertainty should be paramount to environmental uncertainty. Environmental uncertainty is the dominant type of uncertainty in the ITO domain. This could be mainly due to the fact that IT projects have in general a high degree of uncertainty (Nidumolu 1995; Schwartz and Zozaya-Gorostiza 2003). The higher the uncertainty of an ITO transaction, the higher the flexibility of the governance mechanism should be.

Furthermore, this is the first study that shows that transaction frequency has a high influence on the chosen governance mechanism. According to the literature reviews of Karimi-Alaghehband et al. (2011) and Lacity et al. (2011) no other study has found a significant influence of this TCE construct.

Our results suggest that behavioral uncertainty and asset specificity should not be part of a newly developed endogenous theory. The ITO market is characterized with a high degree of competition (Manning et al. 2011). Acting opportunistically always has the danger that it comes out. This would destroy the reputation of the vendor and might even be fatal (Dibbern et al. 2008; Dongus et al. 2014). Therefore, it is quite unrealistic that there is a high danger of opportunistic behavior by the vendor.

The conducted analyses suggest that asset specificity has hardly any influence in the ITO domain. This is opposed to Riordan and Williamson (1985) who argue that it has the hugest influence of all TCE constructs. From the perspective of an ITO vendor, most of the asset specificity is related to human asset specificity. Human assets are quite mobile and can be used easily work for other customers. This is different in manufacturing where a vendor might have invested in specific tools for being able to fulfill the requirements of the customer. Another explanation could be that due to the high demand of ITO during the last years, it is easily possible to find a second best use for an IT asset.

We contribute to practice by examining factors that determine the contract choice. We find that behavioral uncertainty and the danger of opportunistic behavior does not explain the choice of governance mechanism, which is opposed to findings by Gefen et al. (2008) and Gopal et al. (2003). Therefore, clients do not have to focus on trust issues in the ITO domain. Furthermore, we show the influence of client specific characteristics that should be considered while choosing the appropriate type of contract.

This is only a first step towards an endogenous theory of ITO. Other possible constructs and their influence on the choice of governance mechanism should be analyzed.

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Appendix G – Publication P6

Are we already in a mature ITO market? A longitudinal study on the effects of market maturity on ITO vendor project performance

Research-in-Progress

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Abstract

Studies on information technology outsourcing (ITO) have shown different results for the influence of prior interaction and contract type on the project performance of the ITO vendor. The ITO market maturity could provide an explanation for these differences. However, it is not clear how to separate the ITO market into different maturity phases to gain insight into any possible effect maturity might have on project performance. We used a large dataset from an ITO vendor to analyze this research gap. We find that the ITO market has increased its maturity and can be separated into an immature phase, occurring between 1997 and 2001, a transition phase, occurring between 2002 and 2008 and a third phase which occurred after 2008. This identification of different phases of ITO market maturity will contribute to a deeper understanding of the influence of ITO market maturity on the project performance of ITO vendors.

Keywords: ITO vendor, market maturity, project performance, client knowledge, contract type

Introduction

According to a study of Gartner (2013), the global information technology outsourcing (ITO) market will reach $288bn in 2013 with steady growth during the next several years. ITO is defined as the assignment of an IT task to a vendor, who charges a fee for conducting the service (Apte et al. 1997; Lacity and Hirschheim 1993; Loh and Venkatraman 1992). These IT tasks can vary ranging from "simple data entry to software development and maintenance, data center operations and full system integration" (Apte et al. 1997, p. 289). ITO services have become commoditized during the last years (Manning et al. 2011), which increased the competition between ITO vendors. Additionally, clients have gained more experience with the selection of the right vendor having learned from mistakes made in previous relationships (Lacity et al. 2010; Manning et al. 2011). Several studies argue that the ITO market has increased its maturity during the last two decades (Bapna et al. 2013; Dongus et al. 2014; Stadtmann and Kreutter 2009; Suarez et al. 2013; Susarla and Barua 2011). In order to survive in such a market, ITO vendors need to know how factors, such as client knowledge or contract type, contribute to the performance of their projects.

Empirical studies on the influence of client knowledge, which can be approximated through prior interaction, on the project performance of the ITO vendor have shown contradicting results. While most of the studies show prior interaction has a negative influence (Gopal et al. 2003; Hoermann et al. 2014; Schermann et al. 2014), Ethiraj et al. (2005) found a positive relationship. As the dataset employed in these studies cover different maturity phases, we analyze the moderating role of ITO market maturity on the relationship between client knowledge and project performance of the ITO vendor.

Previous studies have found that fix-price contracts have a negative influence on project performance of the ITO vendor (Ethiraj et al. 2005; Gopal et al. 2003), but the datasets in these studies comprised projects conducted prior to 2001, defined as the on-set of ITO market maturity by Susarla and Barua (2011) and Dongus et al. (2014). Dongus et al. (2014) found that the contract choice differs between the immature and mature phase of the ITO market. Therefore, we focus on the moderating role of market maturity on the relationship between contract type and project performance.

We formulated the following research question to address these identified gaps in our knowledge of the influence of ITO market maturity: How d*oes the influence of client knowledge and contract type on project performance of the ITO vendor differ based on the maturity of the ITO market?*

To address our research question it is necessary to divide the ITO market into different phases based on the level of maturity. Susarla and Barua (2011) and Dongus et al. (2014) argue that the ITO market reached maturity after 2001. Other authors have identified 1998 (Suarez et al. 2013) and 2006 (Stadtmann and Kreutter 2009) as the years maturity was reached. Bapna et al. (2013) did not explicitly identify a date, but treated the maturation as a continuous process. These different concepts call for further research.

We conducted an empirical study with a unique quantitative dataset from a German ITO vendor, called ALPHA. The dataset covers all projects conducted by ALPHA between 1995 and April 2014. The extended time period makes it possible to analyze the maturation of the ITO market. The initial dataset contains more than 36,000 projects for about 2,000 different clients. We find that the ITO market has increased its maturity and can be divided into an immature phase, which occurred between 1997 and 2001, a transition phase, between 2002 and 2008, and a third phase which occurred after 2008. Whether this latter phase is a mature or a second transition phase will be addressed in future research.

The remaining sections of this paper are structured as follows. First, we present background information on project performance and ITO market maturity. This is followed by an explanation of our research model and the hypotheses that are examined are developed. We then present the research method and the studies' preliminary results. The paper ends with our plans for future research on the topic.

Background on ITO vendor project performance and market maturity

Project performance

Lacity et al. (2010) reviewed literature on empirical ITO studies. According to their results, only 8 of 741 analyses considered the ITO vendor's business performance as the dependent variable. To approximate business performance, several measures, such as the project profitability (Gopal and Koka 2010; Hoermann et al. 2014; Schermann et al. 2014), the absolute profits (Ethiraj et al. 2005; Gopal and Koka 2012; Gopal and Sivaramakrishnan 2008; Gopal et al. 2003) and the project price (Gefen et al. 2008) have been employed. Project performance is a complex construct influenced by many factors including client knowledge and contract type.

Repeat interactions increase the ITO vendor knowledge of the processes, structures and technologies of the client (Banerjee and Duflo 2000; Chen and Bharadwaj 2009; Mani et al. 2013). Therefore, the vendor better understands the needs of the client and the tasks of relevance for the project (Chen and Bharadwaj 2009). This knowledge should increase project performance, an argument supported by the findings of Ethiraj et al. (2005). Other studies indicate that prior interaction has a negative effect on the project performance of the ITO vendor (Gopal et al. 2003; Hoermann et al. 2014; Schermann et al. 2014). Gopal et al. (2003) argue that their result could be specific to the market analyzed in their study. Another explanation for the negative effect is the increasing complexity occurring in future projects with the same client (Hoermann et al. 2014) or that the vendor from time to time engages in explorative organizational learning activities which have a negative impact on profitability (March 1991; Schermann et al. 2014).

The two prevalent types of ITO contracts are fix-price (FP) and time and material (TM) (Gopal et al. 2003; Lichtenstein 2004). In FP contracts, the ITO vendor agrees to deliver a predefined result and is compensated with a certain fee (Ethiraj et al. 2005). TM contracts are different because the billing is based on the agreed hourly rate and the working hours invested by the ITO vendor (Ethiraj et al. 2005). Previous studies have found that FP contracts have a negative influence on project performance of the ITO vendor (Ethiraj et al. 2005; Gopal et al. 2003). Gefen et al. (2008) did not find a significant influence of the type of contract on project performance.

ITO market maturity

Several studies argue that the ITO market is in a mature phase (Dongus et al. 2014; Stadtmann and Kreutter 2009; Suarez et al. 2013; Susarla and Barua 2011). In general, the theory on industry life-cycle assumes that at a certain point in time a structural change occurs transforming the industry from a growth (immature) phase to a mature phase (Agarwal et al. 2002; Williamson 1975). The immature phase is characterized by high uncertainty, rapid market growth, an increasing number of firms and a low market concentration. The mature phase is associated with low uncertainty, decrease of market growth to a normal rate, domination of the market by a stable number of companies and a high market concentration (Agarwal et al. 2002; Klepper 1996; Klepper and Graddy 1990; Mazzucato and Semmler 1999; Thorelli and Burnett 1981; Williamson 1975). The industry life-cycle can be separated into different phases (Agarwal et al. 2002; Avnimelech and Teubal 2006; Cusamano et al. 2015; Klepper 1996; Klepper and Graddy 1990; Williamson 1975). Cusamano et al. (2015) focus on the lifecycle of service industries and argue that three phases exist: ferment, transition and mature. A similar three-phase model has been proposed by Klepper and Graddy (1990).

According to Susarla and Barua (2011) and Dongus et al. (2014), the ITO market entered into a mature phase after the year 2001. They argue that the collapse of the internet sector acted as an endogenous shock to change the market. However, Suarez et al. (2013) argue that the mature phase began in 1998. Employing a certain point of time for separating the maturity phases assumes that the market matured in a very short timeframe. Bapna et al. (2013) used a continuous time dependent variable for measuring ITO market maturity, which suggests that maturation is an ongoing activity. A transition phase, as proposed by Klepper and Graddy (1990), has only been assumed by Stadtmann and Kreutter (2009) who argue that the ITO market was in a transition phase between 2000 and 2006.

Research model and hypotheses

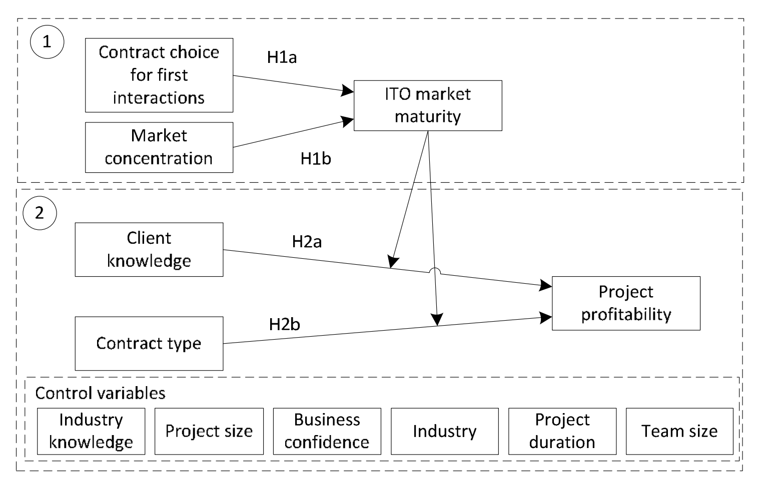

Figure 1. Research model

The previously described different concepts for separating the ITO market call for further research. Based on the market maturity model proposed by Klepper and Graddy (1990) and Cusamano et al. (2015), the following hypothesis is proposed:

H1: The ITO market can be separated into immature, transition and mature phases.

One possibility to measure ITO market maturity is the probability of opportunistic behavior by the vendor. The literature on transaction cost economics argues that the danger of opportunistic behavior is a central construct of exchange relationships (Williamson 1979). According to Williamson (1985) and Hill (1990) the probability of opportunistic behavior increases with uncertainty. Uncertainty makes it difficult to distinguish opportunistic from cooperative vendors (Hill 1990). As previously mentioned, uncertainty in the market differs between the different phases of market maturity (Agarwal et al. 2002; Klepper 1996; Klepper and Graddy 1990). Therefore, the probability of opportunistic behavior is dependent on the market maturity. This view is supported by Argyres and Bigelow (2007) who found that the effect of transaction cost economics is dependent on industry maturity and Dongus et al. (2014) who found that transaction cost economics is only relevant in the immature phase of the ITO market.

Clients try to protect themselves from opportunistic behavior through their choice of contract (Kalnins and Mayer 2004; Susarla and Barua 2011). FP contracts decrease the possibility of the vendor to act opportunistically because the delivery of a predefined result has been agreed upon and any cost overruns are borne by the vendor (Ethiraj et al. 2005; Gopal and Sivaramakrishnan 2008; Lichtenstein 2004).

Asymmetric knowledge between the vendor and the client, which tends to occur during their initial interactions, also enables opportunistic behavior (Williamson 1985). Furthermore, if only a few interactions have occurred, the client does not know whether the vendor tends to act opportunistically (Gefen et al. 2008; Hill 1990). Therefore, the choice of contract for the first few interactions can be used as a proxy for market maturity.

H1a: The ITO market can be separated into immature, transition and mature phases based on the contract choice for the first few interactions between the ITO vendor and the client.

A second possibility for measuring maturity is the market concentration of the ITO market. The number of participants decreases to a stable number in the mature market (Agarwal et al. 2002; Klepper 1996). As the market size does not decrease accordingly, the market concentration can be used as an indicator for market maturity (Agarwal et al. 2002; Mazzucato and Semmler 1999; Thorelli and Burnett 1981). Therefore we formulate the following hypothesis:

H1b: The ITO market can be separated into immature, transition and mature phases based on the concentration of the ITO market.

The influence of ITO market maturity on the relationship between client knowledge and project performance has not yet been examined. Suarez et al. (2013) analyzed the direct influence of maturity on the operation margin of software vendors, but they did not find a significant influence. Karniouchina et al. (2013) argue that the determinants of firm performance are different between the stages of the industry life-cycle. As previously mentioned, results on the relationship between client knowledge of the vendor and project performance are contradictory. The dataset of Hoermann et al. (2014) and Schermann et al. (2014) covers the time between 2004 and 2011 and therefore comes from the mature ITO market according to the definition provided by Susarla and Barua (2011), Dongus et al. (2014) and Suarez et al. (2013). Ethiraj et al. (2005) and Gopal et al. (2003) employed datasets with projects conducted prior to 2001. Their datasets, therefore, might differ in respect to the maturity of the ITO market.

Through repeated interaction with the same client, the vendor gets to know the client's capabilities, its business environment and its culture (Kalnins and Mayer 2004). During repeated interactions with the same client, the vendor tries to develop knowledge about the client which might lead to a competitive advantage and enable the vendor to increase project profitability. However, this is dependent on the maturity of the ITO market.

First, the bargaining power of the vendor decreases with increased maturity. According to Manning et al. (2011), ITO services have become commoditized in recent years. Bapna et al. (2013) found that multi-sourcing increases with ITO market maturity. These developments increase the competition between the ITO vendors and decrease the client's dependence on the vendor which makes switching the ITO vendor easier (Gopal et al. 2003; Manning et al. 2011). Additionally, clients have become more familiar with ITO during the last several years (Lacity et al. 2010).

Second, ITO vendors might be forced to continuously develop new capabilities in a mature market. Schermann et al. (2014) argue that the vendor engages in explorative organizational learning activities with the client from time to time. These projects are associated with higher risk and a lower expected project profitability (March 1991). Because the competition on the ITO market has increased (Manning et al. 2011), ITO vendors might engage in more explorative projects to differentiate themselves from competitors.

Because of changes in vendor bargaining power and the continuous need for vendors to develop new capabilities in a mature market, it is difficult for ITO vendors to leverage client knowledge and demand higher prices. Therefore the following hypothesis has been formulated:

H2a: Client knowledge can be leveraged and therefore increases the project performance of the ITO vendor in the immature ITO market but not in the mature ITO market.

According to findings by Gopal et al. (2003) and Ethiraj et al. (2005), FP contracts, in comparison to TM contracts, have a negative influence on the project performance of the ITO vendor. The datasets used in those studies, however, comprise projects conducted prior to 2001. These results are contradicting: the vendor should be compensated for taking higher risks in FP contracts as it bears all possibly occurring cost overruns (Ethiraj et al. 2005; Gopal and Sivaramakrishnan 2008; Lichtenstein 2004). Perhaps the relationship found by Gopal et al. (2003) and Ethiraj et al. (2005) was due to the immature ITO market where FP contracts are used as a protection against opportunistic behavior for the first few projects (Dongus et al. 2014; Williamson 1985).

FP contracts have a negative influence during the immature phase of the ITO market. The prevalent high uncertainty makes it difficult to estimate the project and therefore leads to contractual gaps which need to be closed during the project (Williamson 1979). These renegotiations create additional costs and lead to lower profitability (Hoermann et al. 2014; Williamson 1979). On the other hand, FP contracts have a positive influence in the mature market because uncertainty is lower. Furthermore, ITO vendors have improved their competences in recent years (Lacity et al. 2009) and should, therefore, be more capable of efficiently managing FP projects.

H2b: FP contracts in comparison to TM contracts have a negative influence on project performance of the ITO vendor in the immature market and a positive influence in the mature ITO market.

Research method and preliminary results

We have already completed the construction of the dataset which is described below. This paper focuses on the separation of the ITO market into different phases of maturity. Therefore, only hypotheses H1a and H1b are examined. Hypotheses H2a and H2b will be addressed in future research.

Research site and data collection

In order to examine the influence of ITO market maturity on the contract choice, we collected quantitative data from ALPHA, a large German IT service provider. ALPHA generates most of its revenue through consulting projects for clients from various industries, but also offers other ITO services such as standard software development and hosting.

The data have been extracted directly from the project controlling system of ALPHA who granted us access to all 36,413 projects conducted between January 1995 and April 2014. The information on the projects is of high quality because it was extracted from the project controlling system of ALPHA, which is also used for billing clients. Additionally, directly accessing quantitative data is not subject to recall bias, which could be a problem in case studies and surveys (Gefen et al. 2008). The dataset contains many variables such as the project profitability, the contract type, the team size, the number of interactions with the client as well as within the industry, the business confidence [based on the ifo index (ifo Institute 2014)], the project start, the project size, the industry of the client and the project duration. We filtered out internal projects, removed projects with incomplete data, and applied trimming (Eriksson et al. 2006) to the project volume, project profitability, project duration and team size in order to remove outliers. This approach is commonly used in empirical ITO vendor studies to clean the dataset (Hoermann et al. 2014; Schermann et al. 2014; Suarez et al. 2013). The first two years of data from the dataset were removed because the first projects for a client should really be the first ones and not simply the start of the dataset. The number of short projects increases towards the end of the dataset as it includes only finished projects. To address this issue, the projects from 2013 and 2014 were removed to have a realistic composition of projects. The final dataset contains 19,895 projects for 1,394 different clients conducted between 1997 and 2012.

Results for contract choice of the first few interactions between client and vendor

Table 1. Descriptive statistics

Variable	Unit	Min	Mean	Max	SD
Number of interaction with client	Number	1	2.25	5	1.34
Business confidence	Points	84.5	103.21	115	7.26
Team size	Number	1	3.01	63	4.32
Project duration	Days	1	194.10	3,071	317.52
Project size	Hours worked	0.5	700.70	46,268.02	2,470.16
Project start	Days since 01.01.1997	1	3,666.67	5,830	1,413.09

In order to examine the first few interactions, we removed projects where ALPHA and the client had more than 5 prior interactions. The created sub-dataset contains 2,968 projects.

Table 2. Linear results of generalized additive model

Dependent variable: contract type (0 = TM, 1 = FP)		
Variable	**Estimate**	**z-Value**
(Intercept)	-0.789375	-1.783
log(Number of interaction with client)	0.039609	0.867
Business confidence	0.009966*	2.522
log(Team size)	0.456609***	10.217
log(Project duration)	-0.066257**	-3.206
log(Project size)	-0.079487***	-3.383
factor (industry) [1]	between -1.301447 and 0.420885	between 0.655 and -5.630
Significance: *** = significant at the 0.1% level; **= significant at the 1% level; *= significant at the 5% level		
[1] because of confidentiality issues the estimates for different industries are not displayed		

In addition to the numerical variables described in Table 1, the dataset contains categorical variables. *Contract type* is measured with a binary variable, where “1” stands for a FP and “0” for a TM contract. The dataset contains 785 FP and 2,183 TM contracts. The variable *Industry* denotes the industry of the client and is based on the ISIC Rev. 4 categorization (United Nations Statistics Division 2015). The projects were conducted for clients from 17 different industries.

In order to examine the influence of ITO market maturity on the contract choice, a generalized additive model for dichotomous dependent variables with a probit link function has been used because it reveals non-linear relationships (Hastie and Tibshirani 1990; Imai et al. 2012). Some of the independent variables have been log-transformed to reduce skewness (Hair et al. 2006). The variance inflation factor did not show any sign of multi-collinearity (James et al. 2013; Sachs and Hedderich 2009). *Project start* has been included in the model as a nonparametric smoothing term. The other variables, whose linear estimates are shown in Table 2, were estimated with standard parametric methods.

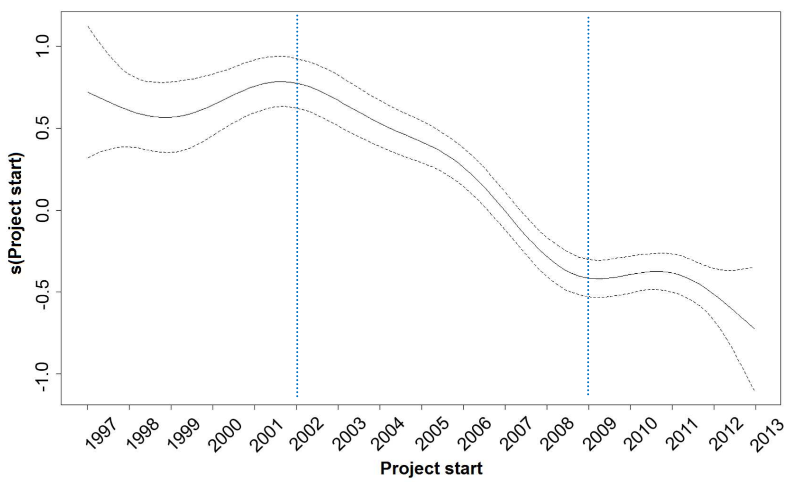

Figure 2. Probability of FP contracts for the first few interactions with the client

Figure 2 shows the non-linear plot for the variable *Project start* of the generalized additive model for dichotomous dependent variables. The dotted lines indicate the 95% significance interval. Figure 2 can be interpreted as the probability to have a FP contract for the first few vendor-client interactions. The graph shows a more or less horizontal relationship until the end of 2001 and then declines until mid-2008. There is a more or less horizontal trend until the end of 2010, then a decline; the 95% significance interval, however, widens.

Results for market concentration

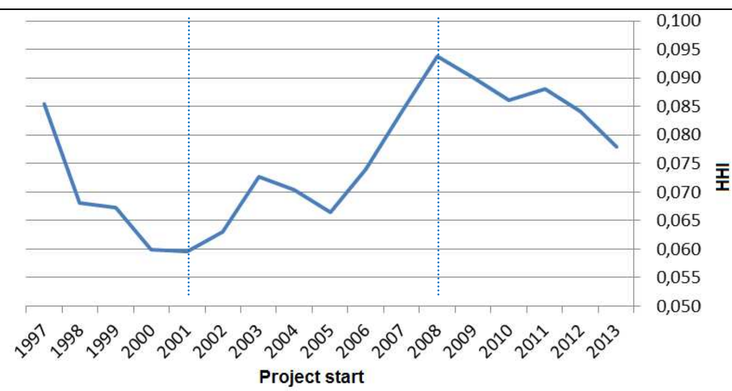

Figure 3. Market concentration of German IT consulting market

Another possibility to analyze the maturity of the ITO market is to calculate its market concentration. The German IT consulting market between 1997 and 2013 was chosen as a proxy because ALPHA is a part of it. For measuring the market concentration, the Herfindahl-Hirschmann-Index (HHI) has been used and is defined as the sum of the square of the companies' market shares (Herfindahl 1950; Hirschman 1945). As it is difficult to get reliable revenue figures for the entire market, a ranking of the 25 largest companies, published yearly by Lünendonk (2015), has been used as a proxy. Bailey and Boyle (1971) found that focusing on at least the eight largest companies in a market does not decrease the validity of the HHI.

For the interpretation of the market concentration, we focused on long-term trends. Therefore, we considered only trends lasting several years. The market concentration decreased from 1997 to 2001, then increased until 2008. The last few years are characterized by a slight decrease of market concentration. The results seem to indicate structural changes occurring at about years 2001 and 2008.

Separation of the ITO market

Hypothesis H1a is supported. It is possible to distinguish three different phases of ITO market maturity based on the probability of having a FP contract for the first few interactions, which is a proxy for expected opportunistic behavior. The first phase lasted until the end of 2001, which is the year of separation between the immature and mature markets as defined by Susarla and Barua (2011) and Dongus et al. (2014). In this phase, the expectation of opportunistic behavior remains constant and high in comparison to the other phases. Therefore, it can be assumed that the ITO market was in an immature state until the end of 2001. The second phase occurred between 2002 and 2008 during which the expectation of opportunistic behavior continuously declined. This can be seen as a transition phase between the immature and the mature market (Klepper and Graddy 1990). As the significance interval increases during the third phase, which started in 2009, it is not possible to determine whether the expectation of opportunistic behavior has been constant or has decreased after 2010. A constant expectation would be a sign that the ITO market has reached maturity while a decrease would argue for a second transition phase.

Hypothesis H1b is supported as well. There was a decrease in market concentration until 2001, indicative of an immature market: the market attracts new entrants which decreases the concentration (Agarwal et al. 2002; Klepper 1996). During the following phase, which lasted until 2008, the market concentration increased. This is characteristic of a transition phase where the number of competitors decreases (Cusamano et al. 2015; Klepper and Graddy 1990). Although in this case the market concentration decreased after 2008, in a mature market, the concentration would remain constant. This decrease is actually a sign of an immature market. Mazzucato and Semmler (1999) analyzed the market concentration of the US automobile market between 1909 and 1995. Their results indicate a high volatility of market concentration for the first decades, decreasing over time with stabilization of the market since the mid-1970s (Mazzucato and Semmler 1999). Transferring these patterns to the ITO market indicates that the ITO market might not have yet reached maturity and still converges towards it.

As H1a and H1b indicate the same three time frames, hypothesis H1 is supported. In general, the maturity of the ITO market has increased. However, it is not clear if the ITO market is already in a mature state or if it is still in a transition phase. Klepper and Graddy (1990) have analyzed the lifecycle of several industries and found that the transition phase can last for several decades. The year 2001 has been defined as the start of the maturity of the ITO market by Susarla and Barua (2011) and Dongus et al. (2014). Our results indicate that a structural change took place, but we cannot conclude that the market is mature after 2001. Bapna et al. (2013) assumed that maturity is a continuous activity and not a certain point of time. We can support this assumption for the transition phase, but not for the other two phases. The structural change of the ITO market in 2008 has not yet been found in the literature. The financial crisis and the following economic downturn, which took place in 2008, seem to have influenced the ITO market maturity. This phenomenon calls for further research.

Limitations and future work

Before we outline our future research on the moderating effect of ITO market maturity, some limitations of our current research should be mentioned. It has been assumed that expected opportunistic behavior is especially important during the first 5 interactions between the vendor and the client. This assumption is based on an interview with a manager from ALPHA. He stated that about 5 interactions are necessary for a client to develop a trusting relationship with the vendor. He reasoned that one or two successful projects (from the viewpoint of the client) could occur because of luck, but it is unlikely that five projects are successful due to chance. In order to mitigate this limitation, models for the first one to nine interactions with a client have been constructed. The non-linear results show the same patterns.

The data used in our study comes from only one company. Therefore, the relationships we found possibly describe the maturation of this company and not of the ITO market. However, ALPHA was founded nearly two decades prior to the start of the dataset and was one of the largest companies of its sector during the entire time covered by the dataset. Therefore, ALPHA was presumably already a mature company at the beginning of the dataset. We plan to perform the same analyses on a second dataset with more than 40,000 projects from an ERP service provider. Up to now, we analyzed the market concentration of the German IT consulting market. To address this limitation, we plan to include data from other ITO market segments as well.

According to Bapna et al. (2013), multi-vendor contracting increases with ITO market maturity. From the perspective of a single vendor, this implies that the project size decreases as more vendors work on the same project. Therefore, estimating the influence of project start on the project size could be used as another indicator of market maturity.

After having shown the feasibility of separating the ITO market into different phases, we will separate the dataset accordingly into sub-segments to address the hypotheses H2a and H2b in our future research. We plan to employ generalized additive models for continuous dependent variables (Hastie and Tibshirani 1990; Imai et al. 2012) because the relationships between some of the independent variables and project performance are highly non-linear (Schermann et al. 2014) With the exception of Schermann et al. (2014), other studies on ITO vendor project performance have assumed linear relationships (Ethiraj et al. 2005; Gefen et al. 2008; Gopal and Sivaramakrishnan 2008; Gopal et al. 2003). In order to answer H2a and H2b, the results for the independent variables will be compared between the different subsets.

Expected contribution and conclusion

We expect to contribute to theory by enhancing current knowledge of ITO market maturity. We identified three different phases of maturity with two separating structural changes. The first one, which occurred in 2001, had already been identified by Susarla and Barua (2011), but the second one, which occurred in 2008, had not yet been identified. We employed two completely different approaches to identify market maturity. The same time frames and points of structural changes have been identified. Therefore the identified phases are quite reliable. When completed, our further research on hypotheses H2a and H2b will contribute to the research stream of ITO vendor project performance. The moderating role of ITO market maturity has not yet been analyzed and should reveal new relationships.

According to our analysis of the dataset, the maturity of the ITO market has increased and we identified three maturity phases occurring between 1997 and 2012. The results indicate a transition phase occurs between the immature and the mature ITO market. Up to now, this phase of the ITO market has only been considered by Stadtmann and Kreutter (2009). The question whether the ITO market is already in a mature phase could not be completely answered and will be addressed in future research.

Acknowledgement

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