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Software Robotics and Artificial Intelligence as an Automation Lever for Management Accounting and Back-Office Automation

Johannes Viehhauser

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Dedicated to my mother.

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Abstract

The optimisation and automation of business processes is becoming increasingly important for corporations in order to remain competitive and to be able to react flexibly to an environment that is changing ever faster. For some years now, a new automation technology called robotic process automation (RPA) has been making its way into corporations and has also attracted a great deal of attention from academia. In a nutshell, RPA constitutes software robots that emulate human work and perform computer tasks in a faster and more efficient way than humans. This dissertation addresses three different issues in the field of RPA, which are presented in three essays. In the first essay, I investigate how to prioritise and select the most suitable RPA candidate processes with an optimal use of resources. As a result, I propose a generalisable method for identifying and prioritising RPA process candidates based on formalised process selection criteria, and expand knowledge of process characteristics by introducing empirically derived factor weights. In the second essay, I examine the impact of RPA on management accounting tasks and techniques, as well as on the organisation and role of management accounting. I present evidence that RPA constitutes a suitable automation solution for management accounting tasks, increases the routinisation and influences the role of management accountants. However, I conclude that the overall impact of RPA is only minor. In the third essay, I enter the infant academic conversation about RPA and artificial intelligence. More specifically, I investigate the extent to which artificial intelligence is complementary and integrable into RPA as well as the resulting effects on the applicability of RPA. I contribute to the literature by clarifying the degree of intelligence and intelligent capabilities of RPA, which is identified as being limited. Moreover, I propose a modular RPA platform approach and present a framework for assessing the level of intelligence of RPA for future research. From a practical standpoint, the essays inform end users and RPA developers to further expand the utilisation of RPA, to advance RPA with focus on artificial intelligence, and to adapt employee profiles accordingly.

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1.1 Motivation

> "Robots are not going to replace humans, they are going to make their jobs much more humane. Difficult, demeaning, demanding, dangerous, dull – these are the jobs robots will be taking." *Sabine Hauert, president and co-founder of Robohub.org and Associate Professor in Robotics at the University of Bristol (Lewis, 2017).*

Robotics and the automation of work have developed rapidly in recent years and are presented in the public discourse as likely to have a massive impact on society, as well as on corporate activities and the way of work (Willcocks, 2020). Above all, modern organisations drive the development of automation technologies, as they are forced to continuously increase their efficiency and productivity, save costs and add value to their business. In this way, they are responding to an increasingly volatile, uncertain and complex world that is changing ever faster (Smids et al., 2020). For example, organisations have been using physical robots in their direct business functions for decades to perform repetitive tasks for hours on end. It is not possible to imagine assembly lines of automotive or semiconductor manufacturers without picturing legions of robots working alongside human workers. The robots in these assembly lines free humans from having to perform mundane, difficult or dangerous tasks (Seasongood, 2016).

For some years now, recent advances in artificial intelligence and machine learning technologies, an improved processing power of computers and the availability of vast amounts of data have enabled the creation of algorithms capable of outperforming knowledge workers (Berry et al., 2009, Gupta et al., 2018). As a result, the robotisation wave has made its way into indirect corporate functions, such as finance, human resources and information technology, and draws much corporate and public attention under the new term robotic process automation (RPA)

(Hofmann et al., 2019, Lacity and Willcocks, 2016). In essence, RPA constitutes a software program called ‘robot’ or ‘bot’ that interacts with existing applications through the user interface of a computer. As the bots are not physical but software robots, a bot is equivalent to one software license. RPA emulates human work in the form of mouse clicks and keystrokes through a range of computer applications. In doing so, RPA performs structured and repetitive tasks in a faster and more efficient way than humans (e.g. Aguirre and Rodriguez, 2017, Güner et al., 2020, Lacity and Willcocks, 2016, Willcocks et al., 2017). A commonly accepted definition for RPA is established by the IEEE Corporate Advisory Group (2017), who defines the technology as “a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions and tasks in one or more unrelated software systems to deliver a result or service with human exception management”.

The history of RPA goes back to the early 2000s, when the first RPA solutions were released. The development of RPA was driven by the banking and insurance industry, which is characterised by high-volume mundane and repetitive transactional processes and tasks as well as by a high level of competition with resulting high cost pressure. This drives the industry to continuously increase efficiency, and paved the way for the development of RPA (Güner et al., 2020, Lacity and Willcocks, 2016). RPA builds on workflow automation and screen scraping technologies, which were first introduced in the 1990s. At this time, more and more organisations started to re-engineer their business processes and process management tools and software appeared. Workflow automation constitutes software that provides a simple solution for automating process steps within a workflow without coding requirements, and screen scraping represents a method for the automated reading of texts and objects from computer screens. However, these technologies were comparably complex and unstable. This is why RPA was developed, based on both technologies, as an easy-to-use and more stable solution (Güner et al., 2020, van der Aalst et al., 2018). In the last few years, RPA has been further developed and is today generating a lot of attention from commercial enterprises as well as academia. According to a recent study from the consultancy Deloitte with 441 executives from 29 countries, the application of RPA in the examined corporations has grown from 13% in 2015 to 78% in 2020, and RPA is now applied across almost all industries and business functions (Watson et al., 2020).

Many academic papers have addressed the question of which activities can best be automated with RPA, and point out that RPA is best suited to automating processes and tasks that are routine, structured, repetitive and rule-based with little exception handling (e.g. Aguirre and Rodriguez, 2017, Lacity and Willcocks, 2017, Penttinen et al., 2018). As RPA is not able to process unstructured or analogue data, inputs should be available in a digital and structured form (e.g. Lacity and Willcocks, 2017, Penttinen et al., 2018, Santos et al., 2019). Moreover, processes and tasks at the interface between systems with the need for frequent access to multiple systems are identified as a good fit for RPA (Güner et al., 2020). Studies from Geyer-Klingeberg et al. (2018) and Wanner et al. (2019) point out that tasks with a high error or failure rate are also well suited for automation with RPA, as the rule-based nature of RPA avoids transactional mistakes or wrong results. Thus, RPA is characterised as well suited to performing 'swivel chair' tasks, whereby workers extract data from one or multiple systems, process the data and add the processed data to other systems (Lacity and Willcocks, 2017). The most prominent examples include logging into systems, extracting data from various file types, moving data, performing checks, filling forms, monitoring events and sending e-mails (Anagnoste, 2017). As a result, human workers are liberated from those mundane tasks and can dedicate their effort to more value-adding and interesting duties. Overall, the core benefits of RPA are identified as an increase of efficiency (Asatiani and Penttinen, 2016, Hallikainen et al., 2018, Santos et al., 2019), a reduction in labour and general costs (Aguirre and Rodriguez, 2017, Hallikainen et al., 2018, Penttinen et al., 2018), an increase in available capacity, which can be used for value-adding tasks that improve productivity (Osmundsen et al., 2019, Plattfaut, 2019), a reduction in error rates (Santos et al., 2019, Wanner et al., 2019), an increase in output quality (Geyer-Klingeberg et al., 2018, Kedziora and Kiviranta, 2018, Wanner et al., 2019) and improved documentation (Lacity and Willcocks, 2017, Wanner et al., 2019). As the costs for RPA are reported to range between 10% and 19% of those of a full-time in-house employee, and 33% to 50% of a full-time off-shore employee, the potential for cost savings is great (Penttinen et al., 2018, Slaby, 2012, Willcocks et al., 2015a). For example, Lacity and Willcocks (2016) examined the implementation of RPA at a large telecommunications company and reveal a three-year return on investment ranging between 650% and 800% resulting from 160 robots. Other studies confirm the high cost savings potential of RPA and quantify cost reductions between 20% and 50% compared to manual operations (e.g. Fernandez and Aman, 2018, Osmundsen et al., 2019, Syed et al., 2020). The benefits described make RPA a promising automation solution for corporations. With the robotisation of indirect corporate functions, RPA has the potential to increase corporate flexibility to respond to fast-changing markets, improve efficiency to counteract competition and reduce the demand for personnel, which can mitigate the 'war for talent' in industrialised countries.

An important question that is often asked is why use RPA and not traditional heavyweight information technology (IT) solutions as part of business process management (BPM). In contrast to BPM, which aims to redesign processes and implement new and complex information systems with potential data interfaces to existing infrastructure, RPA constitutes a comparably easy-to-configure ‘outside-in’ approach and focuses on the automation of existing processes by the use of robots in place of human workers with no need for changes to the IT landscape. RPA qualifies as lightweight IT, since it interacts via the front end and does not impact existing infrastructure, whereas traditional BPM software is characterised as heavyweight IT that operates in an integrated fashion in the back-end on servers or databases (Bygstad, 2017, Penttinen et al., 2018, van der Aalst et al., 2003). RPA therefore serves as a transitional element between traditional IT solutions and human work, and enables a flexible and less complex automation of processes with lower volumes that do not justify the use of complex and costly heavyweight IT (Lacity and Willcocks, 2016, van der Aalst et al., 2018). To delineate the different areas of application, the concept of ‘long tail of work’, which presents different types of business processes, can be used for illustration (cf. Figure 1.1) (van der Aalst et al., 2018). The concept shows that by automating the 20% of process types with the highest volumes, 80% of work can be automated. As the process types are structured and of high volume, it is economically feasible to use traditional BPM methods and heavyweight IT. For example, enterprise resource planning systems (ERPS) constitute a widespread IT solution to automate these process types. However, the remaining 80% of process types that constitute 20% of work and exist as an ideal and fully integrated system landscape is practically impossible, do not justify automation with traditional IT (Hofmann et al., 2019, Syed et al., 2020). These processes, which are often manual, cause high workloads and still need to be handled by human employees without automation as they lack volume. This is where RPA comes into play to automate the large ‘middle part’ of repetitive, but less frequent work. Only very low volume process types on the ‘right side’ continue to be handled manually by humans (van der Aalst et al., 2018).

In addition to the delimitation to BPM, there is the question of how RPA differs from robotic desktop automation (RDA), which is also a technology to automate manual processes. The technological basis of RDA is very similar to that of RPA, however, the concepts differ in terms of operation. RDA provides attended solutions that are assigned to individual employees and operate on their desktops and personal computers. This provides an automation solution for individual employees and front-office tasks for collaborative work between humans and robots. In contrast, RPA automates processes in an unattended and more flexible way and is operated on servers in the back end (Hofmann et al., 2019, Seasongood, 2016).

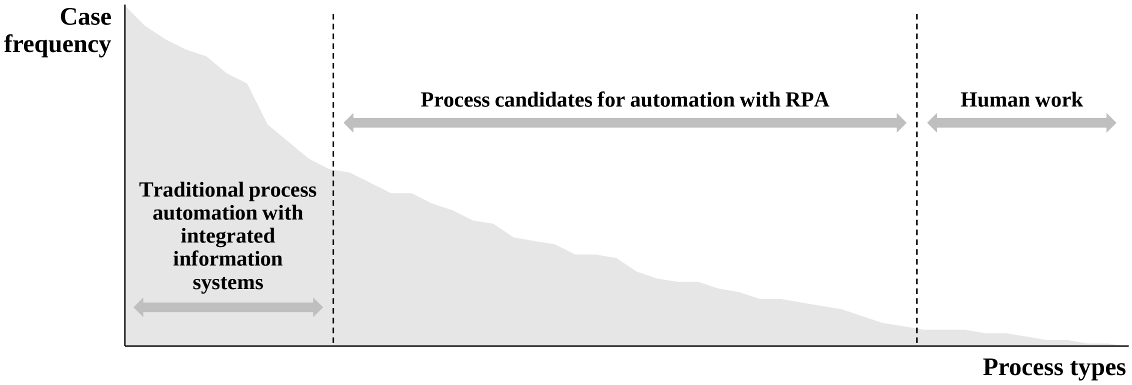

FIGURE 1.1: Concept of 'long tail of work' for classification of RPA application (van der Aalst et al., 2018).

This dissertation enters the young academic conversation on RPA. Research on RPA is of both theoretical and practical interest. It is important to achieve a better theoretical understanding of the technology as well as of its applicability, as research on RPA is comparably scarce and still in its infancy. Moreover, research and commercial studies indicate that RPA exerts a strong impact on organisations, which is why it is also of great practical interest. In particular, this dissertation examines RPA from multiple perspectives based on three research projects, which I present in the following chapters in separate essays.

One of the key challenges in RPA projects is the selection of suitable process candidates. As described above, the application of RPA is limited to process types with certain characteristics, such as rule-based or repetitive, which need to be fulfilled. The selection is critical, as automating unsuitable processes drives inefficiencies, increases failure rates and threatens the success of RPA (Geyer-Klingeberg et al., 2018, Santos et al., 2019, van der Aalst et al., 2018). For this reason, essay I deals with the question of how to systematically identify and prioritise the most suitable processes for automation with RPA.

In the second essay, I put the focus on the application potential and impact of RPA on management accounting. The history section above clarifies that RPA has its roots in the finance sector and is already widely used in corporate functions such as accounting or auditing and in financial shared service centres, which provide a sufficient number of high-volume processes for automation (Cooper et al., 2019, Fernandez and Aman, 2018, Huang and Vasarhelyi, 2019, Kokina and

Blanchette, 2019, Moffitt et al., 2018). However, to date, there has been no research focusing on the application of RPA in management accounting, even though it is heavily dependent upon and impacted by the developments in information technologies. Moreover, commercial studies as well as end users indicate that RPA provides a suitable automation solution for management accounting tasks (Loitz et al., 2020, Quattrone, 2016). The lack of research and high practical relevance makes it an interesting field of research, which I enter with essay II.

In recent years, RPA has also increasingly been discussed in connection with artificial intelligence under new terms such as 'intelligent automation' or 'hyperautomation' (Hofmann et al., 2019, Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019). Research indicates that artificial intelligence expands the fields of application of RPA, and intelligent robots may no longer be rule-based, which allows them to self-reconfigure or learn based on their own experience (Hofmann et al., 2019). Since research on this topic is limited, I take a look ahead in essay III and examine the effects of the integration of artificial intelligence technologies on the capabilities and the applicability of RPA.

In the next section, I present an overview of the historical development of the academic discussion on RPA. Moreover, I introduce the most relevant research streams on RPA as well as on the impact of technologies on management accounting and reveal the research gaps that result.

1.2 Theoretical Background and Literature Context

Research on RPA is comparably scarce and at an early stage. The first broadly acknowledged article about RPA was published in 2012 by Slaby (2012), who researched the impact of RPA on traditional low-cost outsourcing. Even though the article is only a commercial study, many researchers referred to it in the following years. The groundwork for academic research on RPA was laid in 2015 and 2016 by Mary Lacity and Leslie Willcocks. They published multiple case studies about the application of RPA in industries, such as energy or shared services, and business functions, such as the IT function (Lacity et al., 2015a,b, Willcocks et al., 2015a,b, 2017). The year 2016 also saw the publication of the first article about RPA in the telecommunications industry in a scientific journal (Lacity and Willcocks, 2016). Since then, there has been a significant increase in research on RPA, with double-digit articles published annually since 2018. This illustrates the high importance of and increasing interest in RPA not only for practice, but also in science. Research about RPA is mainly published in information systems journals, such as the ‘Journal of Information Technology’, ‘Business & Information Systems Engineering’, ‘MIS Quarterly Executive’ and the ‘International Journal of Accounting Information Systems’. As RPA constitutes a recent and rapidly changing technology as well as a young field of research, many articles are discussed at conferences and published in the respective proceedings. Important conferences are the ‘International Conference on Information Systems’, the ‘European Conference on Information Systems’ and the ‘International Conference on Advanced Information Systems Engineering’.

A large body of fundamental research on RPA investigates the potential for applying RPA in the example use case of concrete industries and corporate functions. For example, Willcocks et al. (2015a) focus their research on the utilisation of RPA in IT functions, Lacity and Willcocks (2016) analyse the RPA implementation and resulting benefits at a large telecommunications company, Aguirre and Rodriguez (2017), Asatiani and Penttinen (2016) and Hallikainen et al. (2018) examine the application potential for RPA at business process outsourcing providers, Suri et al. (2017) and Willcocks et al. (2017) explore the application of RPA in the context of shared service organisations and Vitharanage et al. (2020) investigate the benefits of RPA at an Australian University. In general, it is shown that RPA is very well suited for business outsourcing and shared service providers, as their work is characterised by high-volume and low-cognitive tasks. These are also the industries in which RPA was first applied and on which most studies have been published. For example, finance processes such as accounts payable, accounts receivable or financial reporting, HR processes such as payroll or hire-to-retire, and IT processes such as ticket or database management are often mentioned as suitable candidate processes (e.g. Suri et al., 2017). Besides the applicability of RPA, most examined case studies address the organisation of RPA projects, the RPA readiness of organisations, the identification of RPA processes, prerequisites and challenges for the implementation and operation, resulting direct and indirect benefits, and limitations of RPA. Overall, it is shown that RPA should be regarded as part of a corporation’s long-term strategy and should not be implemented as a short-term solution on a large scale. With regard to the project structure of RPA initiatives, research agrees that projects should start with a pilot phase, often in cooperation with external software providers or consultants, followed by a broad roll out along with the establishment of an RPA organisation. The assessment of RPA opportunities as well as the selection of processes constitutes the most recurring theme in RPA research. Even though research emphasises that a careful and structured process for RPA process selection is critical, most case studies show that the selection is based more on ‘rules of thumb’ and high-level criteria than on clearly defined guidelines and quantifiable methods (Hallikainen et al., 2018, Lacity and Willcocks, 2016, Vitharanage et al., 2020). For example, one telecommunications company examined applies high volume and low complexity as criteria, but does not specify complexity in greater detail (Lacity and Willcocks, 2016). With the case study of a financial services provider, Asatiani and Penttinen (2016) show that processes are selected based on their routine nature and cognitive requirements. The classification, though, is based entirely on employees' judgement and observations. Overall, research suggests that processes with high transaction volumes that require a sufficient amount of resources, high levels of standardisation, high maturity and clearly defined rules are best suited for an automation with RPA. Furthermore, it is advisable to redesigned processes before automation.

The case studies examined also agree with the resulting benefits of RPA, although they differ depending on the application scenario. The benefits that are mentioned most frequently are an increase in efficiency, an improved utilisation of capacities and the elimination of errors (e.g. Lacity and Willcocks, 2016, Suri et al., 2017, Vitharanage et al., 2020). The overall efficiency is improved, as handling and process cycle times, as well as waiting times, can be reduced if operating speed is increased. Moreover, RPA reduces manual and mundane workloads and allows human resources to be deployed and utilised more effectively. As a result, peak workloads can be absorbed and employees can be deployed for more value-adding tasks. For example, Aguirre and Rodriguez (2017) report about a business process outsourcing provider who could improve his capacity by 20% by employing RPA. In the case of a telecommunications company, 35% of back office tasks were automated with RPA that performed up to 500,000 transactions per month (Lacity and Willcocks, 2016). Interestingly, most cases show that RPA has not led to significant layoffs of staff, as they have been redeployed to new tasks or to fulfil the need for additional staff. As RPA works based on clearly defined rules, human errors such as incorrect data transfer or missed steps can be eliminated and the overall output quality and accuracy increases. In addition, RPA offers further advantages such as a decrease in compliance risks, an improved customer service and an overall increasing customer satisfaction (e.g. Suri et al., 2017, Vitharanage et al., 2020). Besides these consistently identified advantages, Vitharanage et al. (2020) reports unanticipated advantages, based on a case study from an Australian university. In that study, RPA is reported to improve the staff knowledge and job satisfaction and enforces compliance with organisational policies. Moreover, disadvantages and implementation obstacles are considered in the case studies. Research identifies the core limitations of RPA as cultural hurdles, a lack of standardisation of processes, the cooperation between IT functions and operational units, a lack of resources and employee mistrust in terms of their fear of losing jobs (e.g. Suri et al., 2017, Willcocks et al., 2017). With their company- and industry-specific findings, the case studies laid the foundation for further and more in-depth research on RPA.

As introduced in Section 1.1, a fundamental question for RPA is which activities to automate and if so, which activities to automate with RPA versus traditional IT. Several studies have examined these problems (e.g. Bygstad, 2017, Penttinen et al., 2018, van der Aalst et al., 2018). Bygstad (2017) introduces the terms heavyweight and lightweight IT to differentiate the two knowledge regimes and to motivate further research. Heavyweight IT is defined as "a knowledge regime, driven by IT professionals, enabled by systematic specification and proven digital technology and realised through software engineering". Examples of heavyweight IT are sophisticated integrated back-end solutions such as ERPS, which are based on databases, servers and integrated software. However, the author points out that integration reaches limits, as complexity increases with the degree of integration and so do requirements for security and resilience (Bannister, 2001, Bygstad, 2017). As a result, many organisations show poorly integrated legacy systems, which impede organisational change and innovation. To overcome this problem, Bygstad (2017) introduces the concept of lightweight IT as "a knowledge regime, driven by competent users' need for solutions, enabled by the consumerisation of digital technology and realised through innovation processes". RPA constitutes a prominent example for lightweight IT and complements heavyweight IT, as it works on the basis of existing infrastructure and supports tasks that cannot feasibly be automated with complex and costly integrated solutions. Penttinen et al. (2018) draw on a case study with a Finish telecommunications company and apply the concept of Bygstad (2017) to examine the choice problem between RPA and heavyweight IT. The authors conclude that the availability of multiple system interfaces, a short duration of implementation with potentially high time criticality, lower project costs and a limited allocation of IT resources are the key selection criteria in favour of RPA. In addition, RPA requires stable user interfaces but can deal with changing back-end system architectures, whereas heavyweight IT relies on the opposite. With regard to process volumes, the findings confirm the concept of the 'long tail of work' from van der Aalst et al. (2018), which states that RPA is best suited for moderate to high-volume processes in contrast to heavyweight IT, which requires very high process volumes for economical operation.

An increasing stream of research contributes to the question of how to organise RPA initiatives and how to select the most suitable process candidates for automation with RPA. In general, the problem of predicting the automation potential of processes is discussed across automation technologies. For example, Koorn et al. (2018) propose a task framework to predict the effects of automation, which also guides the assessment of tasks for an automation with RPA. The authors conclude that creative and adaptive tasks are hard to automate with machines, whereas analytical tasks, routine cognitive tasks and tasks that include information exchange or processing are good candidates for automation. With a focus on RPA, Santos et al. (2019) propose an approach for RPA process selection and implementation in organisations based on a review of five case studies. The approach aims to overcome bad process selection, which is related to inefficiencies and increased failure speed. As a result, the authors suggest that RPA projects should contain four phases, namely (1) process identification, (2) suitability assessment based on predefined selection criteria, (3) design and implementation and (4) testing and evaluation. However, even though these highlight the importance of selecting appropriate processes and suggest multiple decision criteria, they do not specify which criteria need to be fulfilled for a successful RPA project. To overcome the problem, Wanner et al. (2019) introduce a quantifiable method for the selection of suitable RPA process candidates. On the basis of a process preselection, the authors recommend evaluating the automation potential with measurable indicators in a second step, which is supplemented by an analysis of the profitability in a third step. The assessment of the automation potential is based on an indicator system with six criteria. Tasks should be repetitive, have high execution times, a high degree of standardisation, high stability with few exceptions, a low automation rate and a high failure rate. In this regard, this research is the first to introduce mathematically defined and quantifiable decision criteria for RPA process selection. However, the criteria are not exhaustive, neglect the differing importance of influencing factors and the model is only applicable if specific digital log data are available.

Besides, authors focus their research on the organisation of RPA projects within companies and on general success factors of RPA projects. Osmundsen et al. (2019) examine the organisation of RPA initiatives through a case study in the banking, energy and shared services industry. Based on the findings, the authors propose two concepts to organise RPA projects, either with a central body of control that bundles all RPA activities or loosely coupled outside the IT function based on a decentral approach. For the latter, they present advantages in the form of a higher flexibility, improved innovativeness and increased decentral responsibility. In contrast, via a central body the organisation facilitates control and coordination and enables synergies. The cases examined show that a missing or unsuitable control mechanism can result in the wrong processes being automated, as small and easier processes are prioritised over automation of the most important processes. In a case study from the healthcare industry, Plattfaut (2019) confirms the organisation of RPA projects within a central body called 'centre of excellence'. To sum up, existing research shows just how critical it is to define appropriate process selection criteria and has started to investigate the issue. However, it lacks robust, generalisable and quantifiable selection criteria and procedures with which to identify suitable RPA processes. The importance of this topic and the existing research gap motivates essay I, which is introduced in detail in Chapter 2.

All methods described rely on manual analyses and data collection to identify potential process candidates for RPA. For this reason, process identification is very time-consuming and involves a great deal of manual effort, which makes it hard to scale in large organisations (Leopold et al., 2018). To overcome the problem of inaccurate or unavailable documentation in the initial process analysis, Jimenez-Ramirez et al. (2019) describe a lifecycle approach for RPA projects and develop a model for analysing processes based on a screen-mouse-key logger. The model requires that log data with timestamps are collected automatically through monitoring actions of back-office staff. In a second step, the data collected is analysed with image-analysis techniques and automatically transformed into a process model. For the assessment, the criteria high execution frequency, low level of exceptions, few cognitive requirements and high proneness to errors are applied. As a result, accuracy and speed of process discovery in RPA projects can be increased significantly. Geyer-Klingeberg et al. (2018) and Leno et al. (2020) introduce a related concept to automatically discover RPA processes based on existing process data and introduce the term 'robotic process mining'. Robotic process mining constitutes a structured and automated approach that makes it possible to identify and prioritise automatable routines, which are scalable, standardised and repetitive based on log data. The data contain user interactions with web or desktop applications, for example selecting a cell, copying and pasting or editing cells. As the log data is automatically recorded by applications such as ERPS, it can easily be accessed and used to assess the maturity of processes. However, robotic process mining is limited to processes that are executed entirely within a system, as the log data cannot be depicted from multiple independent systems. Another innovative method for identifying RPA process candidates is proposed by Leopold et al. (2018). The authors present an approach based on machine learning and apply natural language processing technologies to automatically identify automation candidates from textual process descriptions, such as process documentations. The algorithm determines whether tasks described in a document are manual, transactional or automated and thereby reduces the manual effort required to assess the degree of automation of tasks.

As this dissertation puts focus on RPA and management accounting (cf. essay II), a detailed look at research on RPA in the finance domain as well as at research on the impact of technologies on management accounting is presented hereafter. A large body of literature focuses on the impact of technologies on management accounting as a corporate function intended to provide financial and non-financial decision-making information to corporate management. In the context of management accounting, change can be caused by both exogenous and endogenous factors (Quattrone, 2016). Examples of exogenous causes are changing market conditions or increasingly competitive market environments, which force companies to adapt to remain competitive (Burns and Scapens, 2000, Burns and Baldvinsdottir, 2005, Byrne and Pierce, 2007). In contrast, research reveals that most changes are caused by endogenous factors, such as innovations in managerial techniques, organisational re-design or growing business complexity, which require more timely and relevant data. Since management accounting relies on the availability and analysis of large data volumes and real-time reporting to be able to cope with complex and fast-paced business environments, research has put particular focus on information technologies as a transformative force for management accounting change (Appelbaum et al., 2017, Burns and Baldvinsdottir, 2005, Granlund and Malmi, 2002, Scapens and Jazayeri, 2003). Several studies have examined the impact of accounting information systems, ranging from simple spreadsheet solutions to integrated information systems such as ERPS, on management accounting (e.g. Granlund and Malmi, 2002, Rom and Rohde, 2007, Taipaleenmäki and Ikäheimo, 2013). ERPS integrate all streams of financial and non-financial information within organisations and provide fast and easy access to data. The connection between ERPS and management accounting is important, as the implementation of new information systems impacts company-wide processes with potential changes to the overall accounting logic. Moreover, data need to be translated by management accounting into relevant information before release (Granlund and Malmi, 2002). Prior studies have made valuable contributions in advancing knowledge on the impact of ERPS on management accounting and the roles of management accountants. For example, Granlund and Malmi (2002) and Scapens and Jazayeri (2003) analyse the implications on management accounting tasks and techniques, Byrne and Pierce (2007), Caglio (2003) and Goretzki et al. (2013) investigate the changing role of management accountants, and Quattrone and Hopper (2005) or Järvenpää (2007) focus on the organisation and culture of management accounting.

Granlund and Malmi (2002) and Scapens and Jazayeri (2003) laid the foundation for subsequent studies on the impact of ERPS on management accounting and the roles of management accountants. In their early studies, the authors conclude that ERPS exert only limited impact on management accounting, since the examined case companies simply transferred their existing principles into the new systems and thus reinforced existing management accounting routines. However, ERPS drove routinisation, broadened the role of management accountants, increased the overall available capacity and enabled a faster and easier access to standardised operational data. In a more recent study, Sánchez-Rodríguez and Spraakman (2012) show that the impact of ERPS on management accounting is greater than identified by prior research, as techniques such as charts of accounts changed and access to non-financial information increased. Overall, the studies introduced show that management accounting is characterised as relatively stable and slow to change. Research explains the stability in economic terms, since changes in management accounting often do not lead to significant net benefits to the organisation, as well as by the routine nature of management accounting, which reflects institutionalised practices that are slow to change and often face resistance (Burns and Scapens, 2000, Granlund and Malmi, 2002). With regard to management accountants, there is a consensus that their roles are impacted by new technologies and get broader with less data gathering and number crunching and more interpretation, strategic decision making and consulting. Management accountants develop more into a hybrid business partner role by adding, for example, IT maintenance and business consulting tasks (Byrne and Pierce, 2007, Caglio, 2003).

As technologies such as ERPS impact management accounting and the roles of management accountants, the question arises whether RPA as a digital imitation of management accountants has the potential to change the discipline even further. However, there is no research on RPA and management accounting. This is interesting, as commercial studies indicate a high application potential of RPA in management accounting (Loitz et al., 2020). Moreover, in recent years, initial studies focussing on RPA and its applicability to and impact on financial tasks have emerged that reveal a high automation potential of RPA. The existing research shows that RPA is an effective tool for automating accounting and auditing processes, as many of them follow clearly defined rules, have a transactional nature and are available in large volumes. Furthermore, it is evident that the profile of accounting staff is affected, and accountants develop towards analytical and IT requirements with less emphasis on data processing (Cooper et al., 2019, Fernandez and Aman, 2018, Huang and Vasarhelyi, 2019, Kaya et al., 2019, Kokina and Blanchette, 2019, Moffitt et al., 2018). Kokina and Blanchette (2019) conducted a multiple-case study on RPA in accounting and finance functions in various industries with a focus on process selection and suitability. Based on the task-technology fit theory, the authors confirm that RPA is highly suitable for order-to-cash and procure-to-pay processes such as payment, invoicing or supplier and customer master data management. The results also confirm the process selection criteria as described above. Moreover, they conclude that RPA affects the profile of accountants. Accountants need to acquire more IT knowledge, for example about RPA development, testing and support, and the role of accountants is evolving more towards analytical tasks. The change in profiles is also confirmed by three case studies in the financial services and accounting services industry (Cooper et al., 2019, Fernandez and Aman, 2018, Kedziora and Kiviranta, 2018). The authors add that the application of RPA provides accountants with more time for value-adding and creative tasks such as performance management, analytics and decision support as RPA avoids non-value-adding manual work. Moreover, they emphasise that the need for adaptability and flexibility increases, as accountants need to be able to continuously adapt to and apply new technologies. Besides the impact on an individual level, the three case studies confirm that RPA is highly applicable to accounting services with an achieved degree of automation of 50% to 80%. For example, RPA was applied to automate tax services, invoice verification and processing tasks, financial report generation or treasury confirmation. As a result, Cooper et al. (2019) showed that processing times could be improved by up to 80% and the level of accuracy was improved from 90% up to 99.9% for the reported cases, since the bots achieve a higher accuracy and work quality (Fernandez and Aman, 2018, Kedziora and Kiviranta, 2018). According to Fernandez and Aman (2018), RPA reduces the overall workload and, therefore, the demand for employees of a global accounting services provider. However, the authors report increased fear among employees that they may lose their jobs, which drives reluctance against RPA. In contrast, Cooper et al. (2019) showed that RPA does not reduce staffing levels and that accountants' job satisfaction increases as routine tasks are eliminated. Huang and Vasarhelyi (2019) and Moffitt et al. (2018) reveal that RPA is also suitable for automating auditing tasks. Based on two case studies, they confirm that audit tasks are suitable candidates for an automation with RPA, since many of them are deterministic, repetitive and follow clearly defined workflows. As a result, non-value-adding tasks could be eliminated, additional capacities could be released, the accuracy of outcomes and services could be improved and auditability and reliability could be secured. Taken together, essay II addresses the identified research gap for RPA in management accounting and examines the impact of RPA on the discipline.

A more recent and forward-looking stream of research focuses on RPA with capabilities based on artificial intelligence, which can be defined as "the ability [of a system] to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption" (Kaplan and Haenlein, 2019). This constitutes a further development of simple RPA, which is limited to the execution of well-structured and routine tasks. In a rather general paper on machines and intelligence, Davenport and Kirby (2016) introduce four levels of intelligence that machines can potentially master, namely support for humans, repetitive task automation, context awareness and learning, and self-awareness. They conclude that machines are capable of supporting humans and automating repetitive tasks, which is essentially done through RPA. However, the authors emphasise that RPA offers only limited context awareness and learning capabilities and self-awareness is not available at all. Based on a literature review on RPA, Syed et al. (2020) clarify that RPA need to become more 'intelligent' in order to be adopted more widely. The authors suggest examining further the combination of RPA with artificial intelligence and machine learning technologies, such as optical character recognition or natural language processing. Combining these could also allow RPA to automate complex processes with unstructured data input, and artificial intelligence could assist with creating no-code RPA development approaches. However, Syed et al. (2020) raise interesting research questions without exploring the issues in detail. One of the first research papers with sole focus on intelligent automation was published by Agostinelli et al. (2019), who analyse different RPA software and propose a classification framework for intelligent automation. As a result, the authors conclude that the examined RPA solutions have only limited intelligence in the form of self-learning abilities. Besides this first attempt, there are no dedicated research papers on intelligent automation, even though many authors emphasise the great importance of RPA and artificial intelligence (e.g. van der Aalst et al., 2018, Plattfaut, 2019, Syed et al., 2020, Wanner et al., 2019). Essay III is motivated by the lack of understanding and the high relevance of RPA and artificial intelligence to examine the impact of artificial intelligence technologies on the capabilities and applicability of RPA.

1.3 Research Overview and Contribution

This dissertation aims to close three important research gaps in order to advance the growing research in the field of RPA. The research gaps were identified based on a comprehensive search within existing research. Moreover, it follows calls for research from recent literature on RPA.

Table 1.1 gives an overview of the three research projects, which resulted in three different essays, and includes the motivation, methodology and key contributions.

In the following, I provide an overview of the research objectives, applied methodologies and main research results and contributions of each essay. In order to answer the various research questions, I apply different research methods. To the best of my knowledge, the methods provide the most suitable foundation for addressing the respective research questions and to contribute to the current state of research and theory about RPA. Moreover, I summarise the main research results and contributions of the three essays that advance our knowledge on the subject of RPA and may guide future research in this field.

In essay I, I focus on the problem of process selection and prioritisation in RPA projects, and suggest a quantifiable model to objectively prioritise suitable RPA process candidates. Research points out that identifying and selecting the most suitable process candidates is critical, as the automation of unsuitable processes drives inefficiencies, increases failure rates and threatens the success of RPA projects (Geyer-Klingeberg et al., 2018, Santos et al., 2019, van der Aalst et al., 2018). For example, Osmundsen et al. (2019) demonstrate in a case study from banking and energy industry that a lack of standardised selection methods leads to an automation of inappropriate processes. As a result, companies waste a considerable amount of time and resources by automating unsuitable processes, which also negatively affects the overall acceptance for RPA. Furthermore, the selection of suitable processes is crucial from the perspective of optimal resource utilisation, since the number of candidate processes usually exceeds the available resources for implementation. Therefore, Geyer-Klingeberg et al. (2018) emphasise the importance of process prioritisation as a critical factor in successful RPA projects.

To overcome the problem of incorrect process selection, researchers have begun to explore the question of how to select suitable candidate processes, as shown in Section 1.2. However, the literature review shows that although general process models are proposed, current research lacks robust, generalisable and quantifiable selection criteria that can be used to identify suitable RPA processes (e.g. Aguirre and Rodriguez, 2017, Jimenez-Ramirez et al., 2019, Syed et al., 2020). Furthermore, research does not examine which criteria must be fulfilled in order to obtain suitable RPA candidate processes (Jimenez-Ramirez et al., 2019, Lacity and Willcocks, 2016, Plattfaut, 2019, Santos et al., 2019). The only research that has, so far, attempted to approach the problem of defining process selection criteria has been published by Wanner et al. (2019). The authors propose a quantifiable method with six process selection criteria to determine the automation potential of processes. However, they lack an exhaustive literature review from which to derive their decision model, and also neglect the varying importance of selection criteria, even though when consulted, experts have pointed out differences in the perceived importance of the criteria. Moreover, the model is only applicable when log data are available. In view of the identified research gap, as well as the high importance of selecting appropriate candidate processes for both academia and practice, I raise the following research question in essay I: ***How can organisations systematically identify and prioritise the most suitable candidate processes for automation with RPA?*** In answering the research question, I am responding to calls for research from van der Aalst et al. (2018), Cooper et al. (2019) and Wanner et al. (2019). The former two shed light on research into processes that are particularly suitable for automation with RPA as opposed to humans. Based on a multiple case study, the latter observe that the perceived importance of process indicators varies. Therefore, they encourage research to further explore weighted indicators for the selection of RPA processes.

To close the identified research gap, I apply an objective-centred design science research (DSR) approach as proposed by Hevner et al. (2004) and Peffers et al. (2007). DSR is a generally accepted framework for designing IT artefacts to solve organisational problems in information systems research. Therefore, it is well suited to addressing the problem of designing a quantifiable method for process prioritisation in RPA projects. The framework consists of several iterative steps, including problem identification, the definition of research objectives, artifact design and development, demonstration, evaluation and communication (Peffers et al., 2007). Based on the research question, I derived selection approaches and criteria for RPA process selection by conducting an extensive literature review as well as 13 expert interviews in line with the recommendations of Webster and Watson (2002) and Eisenhardt and Graebner (2007). The current state of the art of research is examined and combined with findings from the case studies in order to develop the decision support model. To obtain the relative importance of selection criteria, I conducted a survey based on the analytic hierarchy process (AHP) approach with 134 RPA developers, consultants and end users (Saaty, 1990). AHP is based on a pairwise comparison of decision elements and is well suited to structuring multi-attribute decision problems such as process selection in RPA projects (Vaidya and Kumar, 2006). To ensure the operability of the model, it was demonstrated, evaluated and further refined with real-life data from 102 sub-processes and 792 activities from the management accounting department of an international technology company.

As a result, I present a systematic and generalisable method for identifying and prioritising RPA process candidates based on formalised process selection criteria in essay I. To ensure a structured prioritisation of RPA process candidates, I propose a three-step approach, starting with defining the objective and followed by identifying and prioritising the process, and finally selecting the most promising candidates for implementation. The key strength is that the selection is based on a mathematical model to objectively prioritise promising RPA process candidates based on suitability values. With regard to process characteristics, the empirical results suggest that standardisation constitutes the most important RPA criterion, followed by a large volume of transactions, a high maturity of processes and applications, a high degree of manual effort, digital and high-quality data input and a high failure rate. Answering the research question of essay I comes with several noteworthy contributions that extend existing research about process selection in RPA projects. First, I present an industry- and application-independent mathematical model with quantifiable suitability values to assess and prioritise the automation potential of processes for RPA. The model can form the basis for further research on technical process identification and provides decision support for the application of RPA in practice. Second, the research expands knowledge about process characteristics that are particularly important for RPA by introducing factor weights. To my knowledge, this research is the first to introduce weighted factors derived from empirical data as well as an objective and formalised description of the degree of alignment between the criteria and the process. Third, I validate the model by including practical knowledge from expert interviews and a real case from management accounting, which confirms its applicability. The essay also informs managerial practice by providing guidance for selecting the most promising RPA process candidates. As a result, the likelihood of success of RPA projects can be increased and the overall acceptance of RPA can be enhanced.

With essay II, I enter the field of research on management accounting change with technologies as an external transformative force as well as on the applicability of RPA in management accounting. As mentioned in Section 1.2, the question of the impact of technologies such as ERPS on management accounting and on the role of management accountants has generated great interest in research in the past (e.g. Caglio, 2003, Granlund and Malmi, 2002, Quattrone and Hopper, 2005, Sánchez-Rodríguez and Spraakman, 2012, Scapens and Jazayeri, 2003). However, it is evident that the management accounting system and process landscape is still heterogeneous with a high degree of disintegration, manual effort for data handling, inefficiencies and peak workloads at month-end (Dechow and Mouritsen, 2005, Granlund, 2011, Rom and Rohde, 2007). The identified deficiencies suggest that RPA could provide a good solution, as research indicates that RPA is particularly suitable for automating manual and transactional tasks and provides a flexible solution to expand capacities. A high application potential for RPA in management accounting is also confirmed by commercial publications. According to a study by PwC of 141 companies in Germany, Austria and Switzerland, 54% already apply RPA, of which 63% have automated management accounting processes (Loitz et al., 2020). However, to date, no research on RPA and management accounting exists.

Essay II adds to the literature on the impact of technologies and, in particular, on the impact of RPA on management accounting and the role of management accountants. The essay builds on the history of research on ERPS and management accounting change. In particular, it is based on Granlund and Malmi (2002), who initiated research on ERPS and management accounting in 2002. On this theoretical basis, I raise the question of the impact that RPA has on management accounting and whether the introduction of RPA might even be comparable to the introduction of ERPS in the 1990s. The purpose of the essay is to examine the impact of RPA as an innovative automation tool on management accounting tasks and techniques, as well as on the organisation and role of management accounting. As with research on ERPS in the early 2000s, it seems to be the right moment in time to enter the field, as the application of RPA technologies is currently beginning and evolving rapidly, with only few companies having lengthy experience with RPA. Therefore, research can help to better understand the application of RPA in management accounting as well as the benefits that result.

To examine the impact of RPA on management accounting, I apply a cross-sectional multiple case study approach, which is broadly applied to research management accounting change and new phenomena such as RPA and management accounting that lack an established theoretical foundation (Eisenhardt and Graebner, 2007, Yin, 1981). Moreover, it is a proven methodology in information systems research to understand newly emerging technologies in organisations (e.g. Byrne and Pierce, 2007, Conboy et al., 2012, Granlund and Malmi, 2002, Orlikowski and Baroudi, 1991). Five European non-tech companies from various industries that apply RPA in their management accounting departments at various stages of implementation are selected as case companies, and form the unit of analysis of essay II. Moreover, RPA consultants are added to provide a broad cross-company perspective. The research focus is placed on one specific point in time, as RPA is still in an early stage, with no historical data available for a longitudinal study. For data analysis, I build on the definition of management accounting by Rom and Rohde (2007) and adapt it to the peculiarities of research on RPA. The resulting framework allows for a structured analysis based on the four dimensions tasks, techniques, organisation and roles, as well as organisational behaviour. To better understand forces that drive change and continuity in management accounting, I employ the conceptualisation of management accounting change based on the institutional theory by Burns and Scapens (2000). According to Burns and Scapens (2000) as well as Granlund and Malmi (2002), the theory constitutes an appropriate lens to explore the status quo and changes that are occurring in management accounting.

The empirical results underpin the suitability of RPA solutions for management accounting automation. The application of RPA enhances process automation and standardisation, and thus increases the general routinisation of management accounting. As a consequence, the results illustrate that tasks become less transactional with less manual data handling and manipulation effort and the overall efficiency and effectiveness of management accounting increases. However, the cases examined reveal that only a small number of management accounting tasks is automated with RPA to date, and accounting techniques or performance indicators have not been touched. Therefore, I conclude in essay II that the overall impact of RPA is only minor and not comparable to the introduction of ERPS in management accounting or RPA in accounting and auditing functions (Cooper et al., 2019, Huang and Rust, 2018, Sánchez-Rodríguez and Spraakman, 2012). Moreover, the essay yields important insights into the changing role of management accountants. The automation of tasks with RPA makes accountants the recipients of reporting data prepared by RPA and thus further develops their roles from internal data and report generation towards a more analyst and consulting role with advanced IT knowledge. Interestingly, the organisation and the size did not change, even though the results of prior research on RPA would have suggested this (e.g. Lacity and Willcocks, 2016). The essay makes several important contributions. In general, the findings extend knowledge about RPA and management accounting change and initiate academic discussion in this field. Even though a general suitability of RPA for management accounting tasks is confirmed, the impact on management accounting change is identified as only minor. However, as the application of RPA in management accounting is still in an early stage, the impact may increase in future. Second, I propose a task classification with six fields of application for RPA in management accounting. The classification can help guide the selection of management accounting tasks for automation with RPA. Third, I introduce an analysis framework to examine the impact of RPA on management accounting change, which can be used for future research on the subject. From a practical perspective, the results foster corporate executives to apply RPA in management accounting, point out fields of application and identify requirements for future accountants.

Essay III broadens the perspective of research on the impact of artificial intelligence technologies on the capabilities and applicability of RPA. The essay also proposes a definition for intelligence in the context of RPA and discusses the general necessity of intelligence within RPA. Existing research indicates that RPA is becoming increasingly 'smart' by combining it with intelligent features such as image recognition (Hofmann et al., 2019, Plattfaut, 2019) or learning capabilities (van der Aalst et al., 2018, Wanner et al., 2019), which is made possible by advances in artificial intelligence and machine learning technologies, the increasing processing power of computers and the availability of large amounts of data (French, 2012, Gupta et al., 2018). The development seems to be important for RPA, as to date the technology is limited to the automation of well-defined routine tasks based on explicit rules, that do not require intelligence (Plattfaut, 2019, Wanner et al., 2019). With these capabilities, RPA has reached a high adoption as companies still face a lot of manual tasks. However, an important next step for RPA would be to become 'smarter' to be able to work with unstructured data and to perform more complex tasks. Even though it appears to be a major trend in industry and some research papers indicate these features in their outlook sections or as part of literature reviews, in-depth research on the subject is lacking (e.g. Hofmann et al., 2019, Syed et al., 2020). Moreover, the questions exist of whether RPA itself needs intelligence at all or whether it makes more sense to combine it with external intelligence. For example, authors, such as Plattfaut (2019) or van der Aalst et al. (2018) argue that RPA software itself should become more intelligent. In turn, an opposing stream of researchers, such as Hofmann et al. (2019) and Huang and Vasarhelyi (2019) argue that intelligence contradicts the rule-based nature of RPA and intelligence should be provided through external technologies and integrated into platforms. Thus, research dealing with the question of integrating intelligence into RPA is lacking. In this context, it is also important to discuss the general meaning of intelligence for RPA, as 'intelligence' has become a buzzword and is used differently for robots and people (Aleksander, 2017).

The research objective of essay III is, therefore, to shed light on the infant research on intelligent RPA with which I respond to calls for research from Syed et al. (2020) and van der Aalst et al. (2018). Both authors highlight the importance of the topic and call for further research in this area. In particular, I raise the research question of *how and to what extent is artificial intelligence integrated into RPA and which e ects from artificial intelligence have an impact on the capabilities of RPA as well as on its applicability?* The essay employs a multiple case study approach as proposed by Eisenhardt and Graebner (2007). The multiple case study approach is widely used in information systems research and is suitable for researching emerging technologies in organisations such as RPA in combination with cognitive intelligence (Alavi and Carlson, 1992, Conboy et al., 2012, Orlikowski and Baroudi, 1991). The unit of analysis of essay III is the global RPA industry in the year 2020. Based on theoretical sampling, nine RPA software developers and six RPA integrators are selected to cover the market as thoroughly as possible. The software providers contribute state-of-the-art technology knowledge, which is complemented by an application-oriented perspective of the integrators. To facilitate a structured analysis of the level of intelligence of RPA, I utilise a conceptualisation of cognitive intelligence following Gupta et al. (2018) and Modha et al. (2011) as a theoretical lens. The framework is based on the two dimensions information capturing and information processing. As the first dimension, capturing information includes the collection of data and information as well as the perception and observation of the environment. The second dimension, processing information, includes capabilities to analyse and interpret contextual meaning.

Essay III adds to the conversation about RPA and artificial intelligence by clarifying the degree of intelligence of RPA. The results demonstrate that RPA has only very limited intelligent capabilities and, by its nature, remains a rule-based execution engine. Only technologies to process unstructured data input as well as supervised learning capabilities, which increase the efficiency and stability of operations of RPA without affecting its predictability, are added. This confirms the research by Hofmann et al. (2019) and Plattfaut (2019). None of the examined RPA engines fulfil the prerequisites for intelligence, which disproves the hypothesis of RPA being intelligent. In addition, I introduce a platform approach to add cognitive intelligence to RPA. The findings show that adding intelligence modularly via platforms seems to be a promising and flexible solution to cope with the fast-changing and complex developments of artificial intelligence solutions. The essay also yields interesting insights into the applicability of RPA. As the degree of intelligence of RPA increases, the necessity for structured data input, standardisation and process stability is reduced. To sum up, I add to the growing literature on intelligent RPA with several remarkable contributions in essay III. First, I introduce a framework for assessing the level of intelligence of RPA, which can be applied and further developed for future research. Second, I introduce the approach of modular RPA platforms and, therefore, further detail, and operationalise intelligent automation as newly emerging terminology (Hofmann et al., 2019, Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019). Third, I disprove the hypothesis that RPA requires comprehensive intelligence and propose directions for future research to investigate RPA platforms rather than RPA engines. From the perspective of practice, I suggest detailed cognitive capabilities that should be incorporated to further improve the overall capabilities of RPA. This is of particular interest to RPA software providers.

In conclusion, this dissertation makes meaningful contributions to the literature on RPA by enhancing the understanding of process selection and prioritisation in RPA projects, by examining the application potential and impact of RPA on management accounting and the role of management accountants, and by investigating the impact of artificial intelligence technologies on the capabilities and applicability of RPA.

1.4 Structure of the Dissertation

This dissertation is composed of three essays that address RPA from multiple perspectives by answering different research questions. As the essays constitute individual research projects, theoretical background and concepts are partially provided more than once. This allows the reader to review the articles independently of each other.

The remainder of the next chapters is structured as follows. Chapter 2 comprises essay I with the title 'Digging for Gold in RPA Projects – A Quantifiable Method to Identify and Prioritise Suitable RPA Process Candidates', in which I propose a generalisable method to detect, prioritise and select process candidates for an automation with RPA. It is followed by essay II 'RPA and Management Accounting: A Multiple Case Study' in Chapter 3. In this essay, I examine the impact of RPA on management accounting tasks and techniques, as well as on the organisation and role of management accounting. Chapter 4 then provides essay III 'Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation', in which I look ahead and examine the impact of artificial intelligence on the capabilities and applicability of RPA. Finally, Chapter 5 summarises the main overall findings and general conclusions of this dissertation and discusses practical implications, limitations and resulting ideas for future research. The Appendix provides supplementary information for each essay, such as interview questionnaires, detailed numerical and statistical evaluations and further results of the case analyses.

Table 1.1: Overview of the three essays.

Essay	**Essay I (cf. Chapter 2)**	**Essay II (cf. Chapter 3)**	**Essay III (cf. Chapter 4)**
Research question	How can organisations systematically identify and prioritise the most suitable candidate processes for automation with RPA?	How does RPA impact management accounting tasks and techniques as well as the organisation and role of management accounting?	How and to what extent is artificial intelligence integrated into RPA and which effects from artificial intelligence have an impact on the capabilities of RPA, as well as on its applicability, with a focus on suitable task characteristics?
Referring call for research	van der Aalst et al. (2018), Wanner et al. (2019)	Hofmann et al. (2019), Syed et al. (2020)	Syed et al. (2020), van der Aalst et al. (2018)
Research approach	Mixed methods (qualitative, quantitative)	Qualitative	Qualitative
Methodology	Objective-centred design science research approach including literature review, multiple-case study and survey based on analytic hierarchy process approach	Cross-sectional multiple case study	Multiple case study
Unit of analysis	RPA software providers, RPA integrators and end users	Companies from various industries that apply RPA in management accounting at different stages of implementation	RPA software providers, RPA integrators
Main theoretical contribution	Mathematical model to prioritise RPA process candidates; expansion of knowledge about process characteristics; introduction of empirically derived factor weights for process selection	Conclusion of a minor impact of RPA on management accounting change; generally valid task categories with six fields of application; analysis framework for research on RPA and management accounting change	Enhanced understanding of RPA and intelligent capabilities; framework to assess the level of intelligence of RPA; introduction of modular platform approach
Main practical contribution	Guidance for the selection of promising RPA process candidates	Task-specific application potential of RPA; changing role requirements for management accountants	Suggestion of beneficial cognitive capabilities to incorporate into RPA

2 | Digging for Gold in RPA Projects – A Quantifiable Method to Identify and Prioritise Suitable RPA Candidate Processes

Abstract

Robotic process automation (RPA) enables the automation of well-defined and repetitive processes by providing a virtual workforce and therewith extends the robotisation wave from direct areas. Even though RPA draws much corporate attention in recent years, many RPA projects fail or lack behind expectations. A major reason is the automation of wrong processes, mainly driven by a lack of objective methods to select suitable candidate processes. The goal of this paper is to develop a generalisable method to detect, prioritise, and select candidate processes for the automation with RPA. The paper follows the principles of design science research and includes a literature review, expert interviews, and an extensive survey based on the analytic hierarchy process approach with RPA developers, consultants, and end users. As a result, we present a three-step approach and a quantifiable model to objectively prioritise suitable RPA candidate processes based on suitability values. We empirically show that the most important criteria to select RPA candidate processes are a high degree of standardisation and high volume.

Authors: Johannes Viehhauser and Maria Doerr[1]

Status: Working Paper[2]

[1] Master's degree student who assisted with the conduction of the survey

[2] A short version of this paper was presented at the 33rd International Conference on Advanced Information Systems Engineering (CAiSE) 2021 and published in the Lecture Notes in Computer Science (https://doi.org/10.1007/978-3-030-79382-1_19)

2.1 Introduction

Ongoing optimisation and automation of business processes is a vital element of corporate activity when it comes to increasing productivity and competitiveness. Such business process optimisation typically involves tools like standardisation, streamlining, outsourcing, and automation under the application of information technology (IT) and is considered part of business process management (BPM) (Plattfaut, 2019, van der Aalst et al., 2018). However, the degree of process automation achieved by most companies represents only the tip of the iceberg, since only structured processes with high case frequencies are sufficiently economically viable for automation with traditional heavyweight IT solutions (van der Aalst et al., 2018). Accordingly, the vast majority of processes do not justify automation.

For some years now, a revolution in automation has been emerging in the form of robotic process automation (RPA) to address those processes whose medium case frequencies previously did not justify the use of IT resources (Santos et al., 2019, van der Aalst et al., 2018). RPA was made possible by advances in artificial intelligence, machine learning, and optical character recognition and constitutes software robots that mimic human activities to digitally perform tasks on the user interface of a computer system (Lacity and Willcocks, 2016, Mendling et al., 2018, Penttinen et al., 2018). The aim of RPA is to automate existing processes without the need for any major changes to either processes or the existing IT infrastructure. In contrast, BPM places the focus on process re-engineering (Bygstad, 2017, van der Aalst et al., 2018). RPA can be regarded as an evolution from basic automation solutions like straight through processing, since it is more robust to changes, allows enriched logic, and supports more complex processes (Penttinen et al., 2018). Therefore, the software is best suited for performing mundane and repetitive 'swivel chair' tasks, such as transferring data between systems or manipulating and processing data on the basis of predefined rules (Lacity and Willcocks, 2016, Plattfaut, 2019).

One of the key challenges of RPA lies in its ability to select the most promising process candidates, since the automation of unsuitable processes drives inefficiencies, increases failure rates, and threatens the success of leveraging RPA technologies (Geyer-Klingeberg et al., 2018, Santos et al., 2019, van der Aalst et al., 2018). Various authors also point to the lack of standardised methods for analysing and identifying suitable RPA processes (e.g. Aguirre and Rodriguez, 2017, Jimenez-Ramirez et al., 2019, Syed et al., 2020). In addition, there is a lack of well-defined guidelines for prioritising candidates for automation based on critical factors (e.g. Cooper et al., 2019, Santos et al., 2019). As shown by case studies on RPA in the telecommunications, healthcare, and financial services industries, process selection is often based on 'rules of thumb' rather than clearly defined, generalisable, and reliable criteria (Hallikainen et al., 2018, Lacity and Willcocks, 2016, Plattfaut, 2019). The examined companies select processes on the basis of their complexity and volume but do not further specify or quantify the applied criteria. This increases the risk of making poor selection decisions and the project's failure. The importance of careful process selection is also demonstrated by a case study carried out in the banking and energy industry, which reveals a direct connection between the automation of unsuitable processes and the lack of standardised selection methods. This misjudgement results in a considerable waste of time and resources (Osmundsen et al., 2019).

To address the issue of process selection, researchers have begun investigating the question of how to select suitable candidate processes. For example, Jimenez-Ramirez et al. (2019) describe a lifecycle approach for RPA projects and develop a model for analysing processes based on a screen-mouse-key logger. This approach helps overcome the problem of inaccurate or unavailable documentation in the initial process analysis. However, the authors do not specify any selection criteria with which to identify suitable processes. Based on a review of five case studies, Santos et al. (2019) propose a checklist for RPA process selection and implementation. Although they identify multiple decision criteria, they do not examine which of these criteria need to be fulfilled to obtain a successful RPA process. Geyer-Klingeberg et al. (2018) and Leno et al. (2020) introduce process mining as an innovative lever with which to discover processes that are suitable for automation with RPA. If companies have a large amount of data of sufficient quality, they can apply process mining as a structured approach for identifying mature processes with high automation potential. Furthermore, a quantifiable method of selecting RPA processes based on log data, with the goal of short-term value maximisation, is proposed by Wanner et al. (2019). The authors introduce six process criteria and argue that the main goal of RPA is to reduce personnel costs. However, they lack an exhaustive literature review from which to derive their decision criteria and they neglect criteria weights, even though the experts they consult point out differences in the perceived importance of criteria. Moreover, the model is only applicable when log data are available.

To sum up, existing research on process selection in RPA projects lacks robust, generalisable, and quantifiable selection criteria with which to identify suitable RPA processes. Thus, we raise the following research question: *How can organisations systematically identify and prioritise the* *most suitable candidate processes for automation with RPA?* The motivation for this research follows calls for research from van der Aalst et al. (2018) and Wanner et al. (2019). The former shed light on research into processes and their characteristics that are particularly suitable for automation with RPA. The latter observe that the perceived importance of process indicators varies and thus they call for research to further explore weighted indicators for the selection of RPA processes.

To answer the research question, we apply an objective-centred design science research (DSR) approach to develop an objective and generalisable process selection model (Hevner et al., 2004, Peffers et al., 2007). Moreover, we employ the analytic hierarchy process approach (AHP) in a large-scale survey to derive factor weights for process selection criteria (Saaty, 1990). We identify seven criteria and factor weights for process selection in RPA projects. Standardisation constitutes the most important RPA criterion, followed by a large volume of transactions, a high maturity of processes and applications, a high degree of manual effort, digital and high-quality data input, and a high failure rate. The results confirm and extend the criteria proposed by existing research. To ensure the objective prioritisation of RPA process candidates, we introduce a three-step selection approach together with a mathematical model to quantify the process suitability.

This paper makes three noteworthy contributions. First, it presents a mathematical model with quantifiable suitability values to assess and prioritise the automation potential of processes for RPA. Moreover, it extends the knowledge of process characteristics for RPA by introducing factor weights based on empirical data. The findings inform managerial practice by providing guidance for selecting promising RPA process candidates, thus increasing the overall probability of the project's success.

The paper follows the structure proposed by Gregor and Hevner (2013). Section 2.2 introduces BPM and RPA and distinguishes between the two fields of knowledge. Section 2.3 presents the applied research methodology and elaborates on data collection and model development. In Section 2.4, the results of the literature review and expert interviews are discussed along with the deduced selection criteria. Section 2.5 introduces an RPA process selection model and empirically derived factor weights. The model is evaluated by real-life case data in Section 2.6. Section 2.7 concludes with a discussion of key findings, potential limitations, and possible fields of future research.

2.2 Theoretical Background

2.2.1 Introduction to RPA

Most researchers use RPA as an umbrella term for a computer program based on a scripted language for the digital performance of computer tasks (e.g. van der Aalst et al., 2018). According to a common commercial definition established by Tornbohm: "RPA tools perform [if, then, else] statements on structured data, typically using a combination of user interface interactions, or by connecting to application programming interfaces to drive client servers, mainframes or HTML code. An RPA tool operates by mapping a process in the RPA tool language for the software robot to follow, with run time allocated to execute the script by a control dashboard" (Tornbohm and Dunie, 2017).

'Software robots' mimic human activities by imitating manual screen-based manipulations and reacting to events on the screen (Lacity and Willcocks, 2016, Penttinen et al., 2018, van der Aalst et al., 2018). For example, RPA can capture and interpret existing applications for data transaction, manipulate data, trigger responses, and communicate with other digital systems (IRPA&AI, 2017). The robots can either be traditionally programmed, configured using a graphical user interface, or trained on the basis of recorded process steps. It is the ability of RPA to run on a graphical user interface or computer system in a way that a human would do that distinguishes it from traditional back-end automation solutions. RPA can therefore be adapted to interact with a wide range of application interfaces and software systems without the need for any changes to existing applications (Hofmann et al., 2019, Plattfaut, 2019, Wanner et al., 2019). Also, the implementation of RPA is decoupled from IT departments, since robots can be set up by in-house operators on a business level with no in-depth programming skills.

Research emphasises the core advantage of RPA in increasing operational performance by improving the efficiency and effectiveness of operations. This relieves employees from performing non-value-adding work and reduces personnel costs (Hallikainen et al., 2018, Hofmann et al., 2019, Lacity and Willcocks, 2016). Moreover, due to its rule-based nature, RPA increases output quality by eliminating transactional errors and also increases security, auditability, and compliance (Hallikainen et al., 2018, Hofmann et al., 2019, Lacity and Willcocks, 2016, Penttinen et al., 2018).

2.2.2 Differentiation Between RPA and BPM

Business process automation with RPA belongs to the general BPM domain. According to van der Aalst et al. (2003), BPM is defined as "supporting business processes using methods, techniques, and software to design, enact, control, and analyse operational processes involving humans, organisations, applications, documents and other sources of information" (van der Aalst et al., 2003). However, RPA is not regarded as a methodology designed to replace BPM but as a technology that complements it (Lacity and Willcocks, 2016, van der Aalst et al., 2018). The goal of BPM is to redesign processes so as to increase both standardisation and streamlining and also to increase the degree of automation by creating new information systems with data interfaces to an existing infrastructure. In contrast, RPA aims to automate processes on the basis of an existing IT infrastructure by applying robots in place of human workers (Lacity and Willcocks, 2016, Penttinen et al., 2018). The 'long tail of work', introduced by van der Aalst et al. (2018), illustrates the different types of business processes that can be automated using either BPM or RPA (cf. Figure 1.1). Its Pareto distribution implies that by automating 20% of process types, 80% of processes with high frequencies can be automated. The automation of these highly frequent and structured cases is economically feasible using traditional BPM methods. The remaining 20% of processes constitute the 80% of process types that are handled by human employees at the interface between different IT systems and that are highly time consuming. This is where RPA comes into play to automate the large middle component of repetitive, but less frequent work. It thus serves as a transitional element between BPM and human work. Only very low frequency processes and individual cases still need to be handled by humans (van der Aalst et al., 2018).

From a technical perspective, two key characteristics distinguish RPA from BPM. On the one hand, RPA constitutes an 'outside-in' approach with no need for changes to the existing IT infrastructure. The technology operates on the user interface layer and does not require any new applications or complex integration projects. In contrast, BPM relies on the development of new applications, which makes BPM projects more complex, time-consuming, and expensive. On the other, RPA solutions are comparably easy to configure. They can be set up by operating personnel at the business level who do not need programming skills, whereas BPM solutions require IT expertise and the involvement of IT staff (Bygstad, 2017, Dias et al., 2019, Lacity and Willcocks, 2016).

2.3 Methodology

2.3.1 Research Approach

To answer the research question of how organisations can systematically assess the automation potential of business processes with RPA, we employ an objective-centred DSR approach as proposed by Hevner et al. (2004) and Peffers et al. (2007). DSR is a common framework in the field of information systems research used to design IT artifacts to solve organisational problems. Therefore, it is well suited for addressing the problem of designing a quantifiable method of process selection in RPA projects. The applied DSR approach comprises multiple steps. First, the research problem and objective were identified and defined as introduced in Section 2.1. This was followed by the design and development phase, involving data collection, analysis, and model development. A literature review and expert interviews were conducted to derive selection approaches and criteria for RPA process selection (Eisenhardt and Graebner, 2007, Webster and Watson, 2002). The combination of data input from the literature and expert interviews enabled triangulation to avoid biases and to combine theory with practice. Based on these findings, a quantifiable decision support model for RPA process selection was developed. To obtain the weighted importance of the selection criteria, a survey based on the principles of AHP was conducted with 134 participants (Saaty, 1990). With its pairwise comparison of decision elements, AHP is suitable for structuring complex, multi-attribute decision problems such as process selection in RPA projects (Vaidya and Kumar, 2006). Finally, the developed decision support model was demonstrated, evaluated, and further refined to ensure its operability using real-life data from management accounting. In total, two iterations were required until knowledge growth was negligible.

2.3.2 Data Collection and Analysis

2.3.2.1 Literature Review

We conducted a systematic literature review following the principles of Webster and Watson (2002) to derive a comprehensive overview of state-of-the-art research into RPA process selection criteria and application requirements. The review began with a search for publications using the Google Scholar, Springer, Elsevier, ResearchGate, IEEE Xplore, AIS eLibrary, and

ACM Digital Library databases. The following search terms were applied in titles, abstracts, and keywords: *'robotic process automation'*, *'RPA'*, *'process automation'*, *'intelligent process automation'*, *'virtual workforce'*, and *'software robots'*. Next, we performed a backward search by reviewing citations followed by a forward article search citing papers, until no new papers were identified. The literature review resulted in a total of 82 research papers, conference papers, and white papers. To narrow down the results, all papers were reviewed with a focus on whether they specifically address RPA and whether they use peer-review processes typical of high quality journals or conferences. This resulted in a final total of 24 peer-reviewed research articles and conference papers.

2.3.2.2 Expert Interviews

To enable us to include practical insights from industry as well as the latest RPA software developments, we conducted a total of 13 interviews, comprising eight with experts from RPA software providers and five with RPA integrators (cf. Table 2.1). The interviews and analyses took a theory-building, multiple-case-study approach, as proposed by Eisenhardt and Graebner (2007) and Yin (1981). The RPA software providers were identified from existing research (e.g. Cooper et al., 2019, Lacity and Willcocks, 2016, van der Aalst et al., 2018) and based on recommendations obtained from the interviews. The intention was for software providers to contribute their insights into the latest technologies, application requirements, and approaches for process selection. The RPA integrators were proposed during the interviews and selected for their application-driven perspective and experience of implementation challenges.

TABLE 2.1: Overview of expert interview panel.

Company	Position held by interviewee	Origin	Geographical focus
RPA software providers			
Automation Anywhere	IT Solutions Manager	North America	Global
Blueprism	IT Solutions Manager	Europe	Global
Edgeverve	RPA Director	Europe	Global
Nice Robotic Automation	IT Solutions Manager	Europe	Global
SAP	Business Development Manager	Europe	Global
Softomotive	RPA Account Manager	Europe	Global
UiPath	IT Solutions Manager	North America	Global
Workfusion	RPA and AI Director	North America	Global
RPA integrators			
FourNxt	Board Member	Middle East	Middle East
Macros Reply	Head of Product Innovation	Europe	Europe
Roboyo	Board Member	Europe	Europe
Talan	Development and R&D Manager	Europe	Europe
Tao Automation	Board Member	Asia	Asia

The interviews were semi-structured and consisted of three parts: (1) an introduction into the companies' experience with RPA and the capabilities of the RPA solutions provided, (2) a reflection on key motivators for the implementation of RPA as well as resulting benefits, and (3) a discussion of process selection approaches and criteria (cf. Table A.1). The interviews lasted between 30 and 50 minutes. All interviews were recorded and transcribed for subsequent analysis. A within-case analysis was conducted to identify codes for key motivators and process selection criteria, followed by a cross-case comparison to deduce generally valid process selection criteria and their perceived importance.

2.3.2.3 Expert Survey

To derive factor weights with the relative importance for each selection criterion, we conducted a survey based on the principles of AHP developed by Saaty (1990). AHP is broadly used to prioritise goals and attributes and is based on a pairwise comparison of decision elements (Angelis and Lee, 1996, Vaidya and Kumar, 2006). It is particularly suitable for structuring complex, multi-attribute decision problems, such as process selection in RPA projects.

Table 2.2: Overview of dispatched and completed AHP surveys.

Company type	**Number of dispatched surveys**	**Number of completed surveys (% of total)**
RPA software provider	456 surveys	54 surveys (40.3%)
RPA consultant/integrator	200 surveys	64 surveys (47.8%)
End user	55 surveys	14 surveys (10.4%)
Academia	6 surveys	2 surveys (1.5%)
Total	**717 surveys**	**134 surveys (100.0%)**

The survey included general information relating to the participants, for example, the type of company, experience with RPA, and the main motivation for implementing RPA projects, along with a pairwise comparison of decision criteria for process selection. The selection criteria were compared to each other on a scale ranging from 'much less important' (1/9), to 'just as important' (1), and to 'much more important' (9) (Saaty, 1990). This resulted in $n(n-1)/2$ comparisons, with n being the number of criteria. The survey was conducted in July and August 2020 and sent out with personalised links to 717 recipients. The participants were primarily identified from market reports, publications in the field of RPA, and a LinkedIn community on RPA. Altogether 456 developers, analysts, and sales employees from RPA software development firms were included to gain a technology-driven application perspective. In addition, 255 analysts, consultants, and end users from RPA consultancy and integration companies as well as from industry were included to gain an application-driven perspective. Moreover, six surveys were sent to academic RPA researchers. A total of 134 successfully completed surveys were returned, as shown in Table 2.2.

To derive the weighted importance for each of the selection criteria, the relative and normalised eigenvectors were computed for each criterion. The calculation was based on the geometric mean, as it gives more reliable and accurate results than the median or arithmetic mean when multiple respondents are involved. Data validity and consistency were ensured by calculating a consistency index and consistency ratio.

2.4 Identification of Process Selection Criteria

2.4.1 Literature Review

To derive the key process selection criteria covered in the literature, we examine nine case studies on the implementation of RPA in various industries along with seven papers focusing on the organisation of RPA projects, multiple case studies of RPA suitability and implementation challenges, and three literature reviews on RPA. We also looked at five papers with a general focus on RPA.

Several case studies describe the organisation of RPA projects in different industries or business functions from project selection to implementation, in which most authors propose a four to six stage approach (e.g. Asatiani and Penttinen, 2016, Huang and Vasarhelyi, 2019, Jimenez-Ramirez et al., 2019, Kokina and Blanchette, 2019, Santos et al., 2019). All approaches begin by identifying the processes and assessing their suitability, for example, based on process walk-throughs during workshops or analyses of existing process documentations. The literature review reveals that the selection lacks generally valid selection criteria, which range from decisions driven solely by process characteristics to a combination of process suitability and minimum expected savings (e.g. Jimenez-Ramirez et al., 2019, Lacity and Willcocks, 2016, Plattfaut, 2019). Moreover, the identification of candidate processes based on the review of existing documentations turns out to be inefficient and prone to errors, as shown in a case study by Jimenez-Ramirez et al. (2019). As an innovative lever for discovering suitable processes for automation with RPA, Geyer-Klingeberg et al. (2018) and Leno et al. (2020) suggest robotic process mining to identify mature processes of high automation potential based on interaction logs. However, neither paper specifies any formal characterisations of suitable automation routines, their applicability is limited to the availability of log data, and they only include sub-processes for which all prerequisites are fulfilled and that are fully rule-based. After process selection, Huang and Vasarhelyi (2019) propose a potential modification of processes prior to implementation. All other authors build on existing processes and suggest starting directly with the design and implementation of RPA. Also, robots need to be thoroughly tested before they are finally put into operation. The literature review reveals that, although defined on a high-level, research lacks a detailed and universal approach to the prioritisation and selection of suitable RPA processes. The result of this imprecision is shown by Osmundsen et al. (2019) in a case study covering the banking and energy industries. If unsuitable processes are selected, the companies examined continue to waste a significant amount of time and resources until automation is halted. To sum up, the literature review emphasises that there is a clear need to develop a structured approach with which to identify, prioritise, and select suitable RPA processes.

Existing research shows just how critical it is to define appropriate process selection criteria, even though there are differences between the examined cases in terms of which criteria are applied. In most case studies, process identification is generally based on between two and four selection criteria. For example, Lacity and Willcocks (2016) base their selection on volume and complexity, Asatiani and Penttinen (2016) search for routine, low-cognitive, and rule-based processes, and Huang and Vasarhelyi (2019) analyse in line with the criteria well-defined, mature, and repetitive. Taking all analysed papers into account, a high degree of standardisation with clearly defined rules, a clear structure, and no need for human judgement are identified as the most prevalent selection criteria. Also, a high process volume in terms of frequency of execution and time consumption is found to be important, followed by transactional processes at the interface between applications. Moreover, processes that are largely manual with low rates of automation and processes and involved applications that are stable and mature are particularly suitable for automation with RPA. Regarding data input, research emphasises that data must be structured and available in digital form. Finally, processes with high failure rates that are prone to errors are good candidates for RPA. Table 2.3 contains an overview of process selection criteria and their importance based on the number of mentions they receive. The findings are in line with other literature reviews on RPA process selection criteria (e.g. Hofmann et al., 2019, Ivančić et al., 2019, Santos et al., 2019, Syed et al., 2020, Wellmann et al., 2020).

TABLE 2.3: Overview of process selection criteria identified from the literature review.

Selection criteria	Number of mentions	Sources
Standardisation	17	Aguirre and Rodriguez (2017), Asatiani and Penttinen (2016), Cooper et al. (2019), Dias et al. (2019), Geyer-Klingeberg et al. (2018), Hallikainen et al. (2018), Huang and Vasarhelyi (2019), Jimenez-Ramirez et al. (2019), Kedziora and Kiviranta (2018), Kokina and Blanchette (2019), Lacity and Willcocks (2016), Lacity and Willcocks (2017), Mendling et al. (2018), Osmundsen et al. (2019), Penttinen et al. (2018), Plattfaut (2019), Willcocks et al. (2017)
Volume	16	Aguirre and Rodriguez (2017), Asatiani and Penttinen (2016), Cooper et al. (2019), Dias et al. (2019), Geyer-Klingeberg et al. (2018), Hallikainen et al. (2018), Huang and Vasarhelyi (2019), Jimenez-Ramirez et al. (2019), Kedziora and Kiviranta (2018), Kokina and Blanchette (2019), Lacity and Willcocks (2016), Mendling et al. (2018), Osmundsen et al. (2019), Penttinen et al. (2018), Plattfaut (2019), Willcocks et al. (2017)
Automation rate	9	Aguirre and Rodriguez (2017), Asatiani and Penttinen (2016), Cooper et al. (2019), Geyer-Klingeberg et al. (2018), Hallikainen et al. (2018), Huang and Vasarhelyi (2019), Kedziora and Kiviranta (2018), Mendling et al. (2018), Osmundsen et al. (2019)
Stability and maturity	8	Asatiani and Penttinen (2016), Cooper et al. (2019), Geyer-Klingeberg et al. (2018), Huang and Vasarhelyi (2019), Kokina and Blanchette (2019), Lacity and Willcocks (2016), Penttinen et al. (2018), Willcocks et al. (2017)
Digital data input	8	Aguirre and Rodriguez (2017), Cooper et al. (2019), Dias et al. (2019), Huang and Vasarhelyi (2019), Kedziora and Kiviranta (2018), Kokina and Blanchette (2019), Lacity and Willcocks (2016), Penttinen et al. (2018)
Failure rate	4	Asatiani and Penttinen (2016), Geyer-Klingeberg et al. (2018), Jimenez-Ramirez et al. (2019), Lacity and Willcocks (2017)
Structured data input	3	Cooper et al. (2019), Huang and Vasarhelyi (2019), Kokina and Blanchette (2019)

The economic evaluation of candidate processes based on a cost-benefit analysis is identified as a further dimension of the selection process. Since RPA projects are investments, the most prevalent indicator used to select processes is the return on investment (ROI) (e.g. Cooper et al., 2019, Hallikainen et al., 2018, Plattfaut, 2019). In general, the possible savings from RPA projects are highly promising. For example, Willcocks et al. (2017) report an ROI of between 650% and 800% over the course of a three-year RPA project at a telecommunications provider. It is essential to have an appropriate baseline for measurement as well as a suitable ROI metric by which to quantify the results in order to be able to measure the success of RPA (Hallikainen et al., 2018, Kokina and Blanchette, 2019). The literature shows that there are various ways of conceptualising and measuring the ROI. The most widespread indicator is the measurement of efficiency or productivity gains in terms of headcount savings. Moreover, quality improvements and error reductions, an increase in availability, the performance of time-critical processes, or an increasing level of compliance can serve as additional indicators for an ROI calculation (e.g. Cooper et al., 2019, Kokina and Blanchette, 2019, Lacity and Willcocks, 2016). According to Asatiani and Penttinen (2016), economic evaluation should be done separately to process identification. This is also confirmed by Willcocks et al. (2017), who argue that the selection of suitable processes should be concentrated on first, since a business case will then follow naturally with almost all suitable RPA processes.

As a basis for developing our model for process selection in RPA projects, we build on the reference process selection criteria introduced by Wanner et al. (2019). Based on a literature review of six RPA case studies and interviews conducted with RPA experts, mainly from RPA service providers, the authors identify six process selection criteria to determine the automation potential of the following processes: high execution frequency, long execution time, high degree of standardisation, high stability of processes, high failure rate, and low automation rate (cf. Table 2.4). The proposed criteria are, to our knowledge, among the first company- and industry-independent indicators to examine the selection of RPA process candidates. This presents a viable foundation for the coding of our findings. However, as the criteria are not exhaustive and the mathematical descriptions are only applicable to specific log data, we propose refined mathematical definitions and complement the criteria with a digital and structured data input (cf. Section 2.5.2).

Table 2.4: Overview of process selection criteria as proposed by Wanner et al. (2019).

Process selection criteria	Definition
Execution frequency	Highly repetitive processes with high execution frequency
Execution time	Processes with long execution times
Degree of standardisation	High degree of standardisation of processes with clearly defined rules
Stability of processes	Processes with high stability, low probability of exceptions, and predictable outcomes
Failure rate	Processes with high failure rates or poor output quality
Automation rate	Manual processes with a low automation rate

2.4.2 Expert Interviews

To incorporate practical insights, we conducted 13 interviews with experts from RPA software providers and RPA integrators. The results reveal that all software providers and integrators have structured approaches for identifying RPA process candidates and setting up internal RPA organisations for establishing RPA in the companies. Many of the cases assessed suggest the definition of an automation target as the first step of the automation journey. This step is barely discernible in existing research but turns out to be an important starting point, since it is essential to define the goal of automation, for example, saving headcounts or increasing capacity, as a basis for the selection of suitable candidate processes. Next, the experts propose the identification of process candidates based on a feasibility analysis. Potential processes are identified, analysed, and recorded, for example, in process templates. The analysis serves as a prerequisite for the subsequent assessment of predefined process characteristics, which results in a ranking of all processes according to their suitability. The suitability analysis is followed by an economic assessment of promising process candidates. This includes the development of business cases for the most promising processes, prioritisation based on economic criteria, and the final selection of processes.

It is clear that even though high-level proceedings are defined, almost all RPA providers and integrators lack any clearly defined, objective criteria and assessment models for the selection of process candidates. As a general rule, complexity serves as an approximation for assessing process suitability. However, the operative assessment is, for the most part, not based on objective and measurable criteria, but on subjective evaluations. Most experts define low complexity in terms of such criteria as high degree of standardisation with clearly defined rules and no human judgement, structured data input, high stability of processes and applications, appropriate number of interfaces, and digital data input. Other crucial criteria are high volumes and repetitiveness. The interview findings confirm the most important process selection criteria as identified in the literature review. In addition, they support the call for an objective process selection model.

The economic assessment of process candidates follows varying approaches, ranging from the definition of ROI thresholds to simple headcount targets for each RPA process. In general, the economic perspective should follow the initially defined automation goal. The findings of the interviews demonstrate that cost reduction through personnel reductions, quality improvement, capacity improvement, back-sourcing of processes, and the performance of time-critical processes are the main motivators for applying RPA. To calculate the economic indicators, the experts focus on such criteria as process volume, frequency of repetition, failure rate, and automation rate. Both, process selection criteria and motivators are in line with existing research (cf. Section 2.4.1).

2.5 Development of a Process Suitability Model

2.5.1 Conceptual Process Selection Approach

The analyses show that RPA projects call for both a structured process to identify and select suitable RPA process candidates and for an objective and quantifiable indicator system for identifying suitable process candidates (e.g. Asatiani and Penttinen, 2016, Jimenez-Ramirez et al., 2019, Santos et al., 2019). We therefore propose a three-step process selection model with which to identify and prioritise business processes for RPA (cf. Figure 2.1).

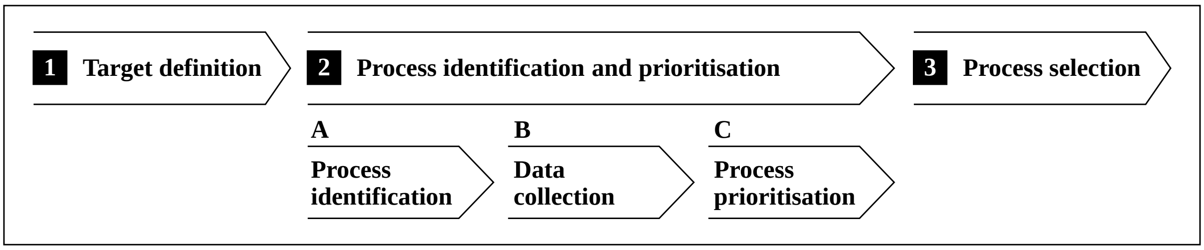

Figure 2.1: Process selection approach for RPA projects.

The proposed selection approach starts by defining the automation objectives. This involves strategic decisions in line with company goals regarding the preferred process automation technology and the definition of objectives on an operational level. Clearly defined objectives are important, because they guide the overall selection process and serve as an appropriate baseline from which to measure and evaluate the project's success (Hallikainen et al., 2018, Kokina and Blanchette, 2019, Santos et al., 2019). The most common objectives of RPA are personnel savings and quality improvements that can be achieved by reducing errors and attaining a higher output quality. Other objectives frequently mentioned are increasing availability and capacity, performing time-critical processes, improving compliance and security, and back-sourcing critical processes.

The second phase consists of process identification (A), data collection (B), and process prioritisation (C). First, a high-level preselection of potentially relevant processes is needed to deal with the large amount of processes within organisations (Jimenez-Ramirez et al., 2019, Lacity and Willcocks, 2016). This can be carried out in workshops, using suggestions by operational employees, or by employing innovative methodologies such as process mining. It is crucial to introduce high-level criteria to guide the process. For example, the criteria of clearly defined rules and high volume can serve as a first approximation to narrow down the selection. The identification process should be conducted by experienced RPA specialists and supported by employees with operational knowledge. Process preselection is followed by data collection to obtain reliable data points as a basis for the process prioritisation model. As shown by Jimenez-Ramirez et al. (2019), data collection from existing documentation has been found to be inefficient and prone to errors and should therefore be avoided. Rather, data collection should be based on, for instance, available user interaction data, system protocols relating to, for instance, volumes or failure rates, process walk-throughs, or standardised templates. The next step is process prioritisation, which constitutes the core element of the proposed approach, its purpose being to detect the most promising process candidates. Process prioritisation is based on the mathematical model introduced in Section 2.5.2 and uses the quantifiable and weighted selection criteria from Section 2.5.3. As a result, all preselected processes are quantified and assessed according to their suitability for automation with RPA.

In the third phase, the most suitable processes are selected for implementation. The selection is based on the most promising process candidates from phase two and is supplemented by an economic evaluation. The proposed model already incorporates economic feasibility criteria, such as high volume, standardisation, maturity (to reduce implementation and maintenance effort), and error rate (to reduce quality costs). To compare the processes from an economic standpoint, the calculation of business cases based on standardised indicators such as return on investment is recommended (e.g. Cooper et al., 2019, Geyer-Klingeberg et al., 2018, Willcocks et al., 2017). According to Asatiani and Penttinen (2016), economic evaluation should be conducted separately from process identification. This is also confirmed by Willcocks et al. (2017), who argue that the selection of suitable processes should be concentrated on first, as a business case follows naturally with almost all suitable RPA processes. Since economic indicators differ depending on the automation objectives, and since companies frequently use specific internal investment indicators, these are not included in the model.

2.5.2 Prioritisation Model for Ascertaining RPA Process Suitability

To ensure an objective selection of suitable RPA process candidates for multiple scenarios, we introduce a mathematical model for quantifying and prioritising RPA process candidates based on weighted suitability criteria. The model aims to enable a detailed understanding of potential process candidates and to prioritise the most suitable processes as a basis for the selection for implementation.

Table 2.5: Model notation.

Variables	Definition
A_p	Number of activities in process p
S_p	Suitability value of process p
U_p	Number of sub-processes in process p
V_p	Number of variants of process p
c_1	Constant 1 (s-curve formulation)
c_2	Constant 2 (s-curve formulation)
e_v	Error rate of process variant v
f_{ip}	Fitness value of factor i for process p
n_v	Number of repetitions of process variant v
t_a	Duration of activity a
w_i	Eigenvector of the relative importance of factor i
b_a	= 1, if data input for activity a is available with sufficient quality, 0 otherwise
d_a	= 1, if data input of activity a is digital, 0 otherwise
m_a	= 1, if an activity a is manual, 0 if activity a is automated
s_a	= 1, if an activity a is clearly defined and standardised, 0 otherwise
x_{av}	= 1, if activity a is required in process variant v, 0 otherwise
y_{au}	= 1, if activity a belongs to sub-process u, 0 otherwise
z_a	= 1, if an activity a is not expected to change, 0 otherwise

We introduce formal notations for our model (cf. Table 2.5), in which a process p consists of V_p process variants v. Each process can be decomposed into U_p sub-processes u and A_p activities a. Moreover, each process selection criterion is defined by a factor index i. To derive the overall process suitability value S_p of a process, all factors are quantified and normalised to an eigenvector ranging between 0 and 1 and weighted with the derived factor weights from Section 2.5.3. Equation 2.1 provides the suitability value for each process, which serves as a basis for deriving the most suitable process candidates.

$$S_p = \sum_{i=1}^{7} (w_i \cdot f_{ip}) \tag{2.1}$$

The analysis reveals that a high degree of standardisation is the most important selection criterion for RPA process candidates. In the context of RPA, standardisation refers to processes that follow a predefined structure, can be decomposed into sub-processes without misinterpretation, and for which all decisions rely on clearly defined rules with no ambiguities (e.g. Asatiani and Penttinen, 2016, Geyer-Klingeberg et al., 2018, Lacity and Willcocks, 2016). Processes with a high degree of standardisation reduce the implementation effort, increase the speed of implementation, and raise the overall probability of project success, and it is this that makes them the most promising RPA candidates (Geyer-Klingeberg et al., 2018, Syed et al., 2020). Hence, standardisation reduces the overall cost of RPA, as the reduced complexity means that fewer exceptions need to be covered. Particularly in the initial phase, research recommends selecting processes that have no need for further standardisation or adjustment (Huang and Vasarhelyi, 2019, Syed et al., 2020). Equation 2.2 conceptualises standardisation as the share of a process's sub-processes for which all activities s_a of the sub-process follow clearly defined rules. The equation excludes sub-processes for which not all activities have been standardised in favour of fully standardised sub-processes. Standardisation is normalised on the basis of the number of repetitions n_v of activities and their duration t_a.

$$f_{1p}=\frac{\sum_{u}^{U_p}(\sum_{v=1}^{V_p}(\sum_{a=1}^{A_p}(t_a \cdot n_v \cdot y_{au}))) \cdot (\min_{a \in \{1,\ldots,A_p | y_{au}=1\}} s_a)}{\sum_{a=1}^{A_p} t_a} \tag{2.2}$$

The second most important process selection criterion is identified as a high volume of processes in terms of execution frequency and execution time. We define volume as the total execution time of a process, i.e. the product of the time required for the performance of a process and the frequency of repetitions (e.g. Dias et al., 2019, Lacity and Willcocks, 2016, Penttinen et al., 2018). Volume is particularly important, since the automation of high-volume processes helps to maximise the benefits of RPA, leverages the potential for cost reduction, and introduces an economic perspective (Lacity and Willcocks, 2016, Santos et al., 2019, Syed et al., 2020). Equation 2.3 operationalises volume based on the execution time of an activity t_a and the number of repetitions n_v. The equation is based on an s-curve formulation to ensure that low-volume processes are valued with lower impact than high-volume processes. Moreover, as suggested by Lacity and Willcocks (2016), we introduce a threshold value as a target volume for processes. The threshold, as the upper limit of the s-curve, can be set individually by modifying the constants c_1 and c_2.

$$f_{2p}=\frac{1}{(1+e^{-c_1 \cdot (\sum_{v=1}^{V_p}(\sum_{a=1}^{A_p}(t_a \cdot x_{av})) \cdot n_v)})^{c_2}} \tag{2.3}$$

The results of the analysis further suggest that the suitability of a process depends on its current automation rate. Geyer-Klingeberg et al. (2018) argue that processes with a high share of manual activities offer greater and faster economic benefits than processes with a high degree of automation. For our model, we define manual effort as the extent to which activities m_a have not yet been automated (cf. Equation 2.4).

$$f_{3p} = \frac{\sum_{a=1}^{A_p} m_a}{A_p} \tag{2.4}$$

We have also ascertained that the maturity of a process is a further critical determinant for process selection in RPA projects. Wanner et al. (2019) consider mature processes as processes with high stability, a low probability of exceptions, and predictable outcomes. According to Penttinen et al. (2018), the vulnerability of the information systems and interfaces involved are particularly critical for RPA. By considering the disadvantages of potential future changes, the overall risk of adjustments or even the failure of an entire RPA project can be mitigated. The automation of stable processes also has a positive impact on the long-term operational costs of RPA. Therefore, we define maturity as the stability of a process and the involved systems with low vulnerability to changes and updates. As with manual effort, we measure maturity as the share of activities z_a within a process that are not prone to changes (cf. Equation 2.5). Changes can take place both within the activity itself, with regard to its position within the sequence of activities, resulting in different inputs and outputs and within the required IT systems and interfaces.

$$f_{4p} = \frac{\sum_{a=1}^{A_p} z_a}{A_p} \tag{2.5}$$

Our analysis reveals that the availability of digital data input is also critical for RPA process selection. Huang and Vasarhelyi (2019) state that data must be compatible with RPA requirements and they need to be available in a digital format or at least be transferable to a digital format. We therefore argue that processes are suitable to RPA if their data are available in a digital format. This extends the selection criteria proposed by Wanner et al. (2019). However, the importance of digital data input is clearly confirmed and therefore needs to be included in the model. We define digital data input as the degree to which the data are available in non-analogue, digital form. Equation 2.6 provides an operationalisation as the share of activities d_a with an available digital data input.

$$f_{5p}=\frac{\sum_{a=1}^{A_p} d_a}{A_p} \tag{2.6}$$

Besides being in digital format, the required data also need to be available in a structured, consistent, and standardised form (Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019). High quality input data increase performance accuracy, prevent errors, and reduce implementation and processing costs. We therefore include input data quality in our model and further extend the selection criteria proposed by Wanner et al. (2019). Equation 2.7 defines quality of input data as the share of activities b_a with sufficient data quality from the total number of activities within a process. The data required for each activity must be unambiguous and with a low probability of exceptions, and they must be usable by RPA without any manual or human intervention.

$$f_{6p}=\frac{\sum_{a=1}^{A_p} b_a}{A_p} \tag{2.7}$$

Finally, processes with a high failure rate are identified as suitable candidates for automation with RPA and included in the model. Automating processes with high error rates reduces quality costs and potential rework expenditures, thus increasing overall performance (Geyer-Klingeberg et al., 2018). We operationalise failure rate with Equation 2.8 and define it as the degree to which a process variant e_v is prone to errors. The calculation should be based on actual historical quality data.

$$f_{7p}=\frac{\sum_{v=1}^{V_p}(n_v \cdot e_v)}{\sum_{v=1}^{V_p} n_v} \tag{2.8}$$

2.5.3 Identification of Factor Weights

To derive factor weights for each process selection criterion, we sent out a survey to 456 developers, analysts, and sales employees at RPA software developers, as well as 255 consultants and end users, and six RPA researchers. A total of 134 completed surveys were returned (cf.

Section 2.3.2.3). To derive the weighted importance of the selection criteria, the relative and normalised eigenvectors for each criterion were calculated on the basis of the geometric mean.

An analysis of the relationship between the level of experience with RPA (ranging from no experience to extensive experience) and process selection criteria reveals that standardisation is valued more highly by experienced participants than by inexperienced ones with a significance level of 5% (cf. Table A.2). Because the literature review, interviews, and survey conclude that standardisation is the most relevant factor, the results indicate that the assessment of inexperienced participants are unreliable and potentially bias the outcomes. We therefore adjust the calculation of the eigenvectors by removing seven participants with little or no experience in RPA. Also, one participant was removed who answered the entire survey without changing the responses from the given neutral default assessments.

The analysis of the results shows that a high degree of standardisation constitutes the most important RPA process selection criterion, with an eigenvector of 0.23 (cf. Table 2.6). This is confirmed by the statistical analysis, which reveals that standardisation is significant at a 1% level compared to all other attributes (cf. Table A.3). Standardisation is followed by a high volume of transactions in terms of the time required to perform processes and the frequency of repetition, with an eigenvector of 0.17. The results are in line with the literature review, in which both attributes are detected the most (e.g. Dias et al., 2019, Hallikainen et al., 2018, Lacity and Willcocks, 2016). The four criteria of high maturity of processes and applications, high degree of manual effort, and digital as well as structured data input can be regarded as being equally important, with eigenvectors ranging between 0.11 and 0.14. This is also confirmed by the statistical analysis. The criterion of high failure rate is valued with an eigenvector of 0.10 and is thus somewhat less important than the previously mentioned attributes.

To ensure data consistency and reliability, a consistency index and ratio are applied, as suggested by Saaty (1990). The ratio indicates the "consistency of the judgements relative to large samples of purely random judgements". The author suggests that if the consistency ratio exceeds 0.1, the set of judgements may be too inconsistent to be reliable and too close to randomness. The result for our sample would be a consistency index of 0.04 and a consistency ratio of 0.03. This underlines that the derived eigenvectors are consistent and non-random (Saaty, 1980, 1990).

Table 2.6: Process selection criteria and derived factor weights (eigenvectors).

Selection criteria	**Definition**	**Eigenvector of relative importance**
Standardisation	The process follows a predefined structure, can be decomposed into sub-processes without misinterpretation, and all decisions rely on clearly defined rules without ambiguity	w_1 = 0.23
Volume	Total execution time of processes as a product of the time required for the performance of the process and the frequency of repetition	w_2 = 0.17
Manual effort	The extent to which the steps within the current process are not (yet) automated	w_3 = 0.14
Maturity	Stability of processes and involved systems with a low vulnerability to changes and updates	w_4 = 0.13
Digital data input	Degree to which the data required for performing a process is available in non-analogue, digital form	w_5 = 0.12
Input data quality	Required data are unambiguous, with a low probability of exceptions, and can be used by RPA based on predefined rules without manual intervention	w_6 = 0.11
Failure rate	Degree to which a process is prone to errors	w_7 = 0.10

2.6 Application of the Model to a Real Case

To demonstrate and evaluate the RPA process suitability model, we applied the model to process candidates in the management accounting department of an international technology company. The company began its RPA journey two years ago at its central headquarters in Germany. After successfully implementing RPA with high volume processes, including in the accounting department, and establishing an RPA centre of excellence, they began considering further leveraging RPA in the management accounting department. Management accounting seemed promising, because the company faced a high workload of manual and repetitive work at the interface between systems, despite applying an enterprise resource planning system and customer relationship management software along with business intelligence tools and other applications. Moreover, it suffered from a peak workload during month-end. Therefore, the company set the target of freeing up employee capacity for value-adding work by implementing RPA (Step 1).

To identify RPA process candidates (Step 2), we began by introducing RPA to all employees in the management accounting department and inviting them to identify potential processes. The proposed criteria from Section 2.5.2 served as a guideline. This enabled us to gather nine process candidates, for which we collected data by measuring the execution times and frequencies of each activity, observing employees performing processes to obtain assessments of the rule-based nature of each activity, and collecting system outputs, such as error rates. Data points for a total of 102 sub-processes with 792 activities were ultimately collected and analysed. The collection process revealed that the proposed model works particularly well when no log data are available. This holds for processes in management accounting that leverage multiple systems and applications.

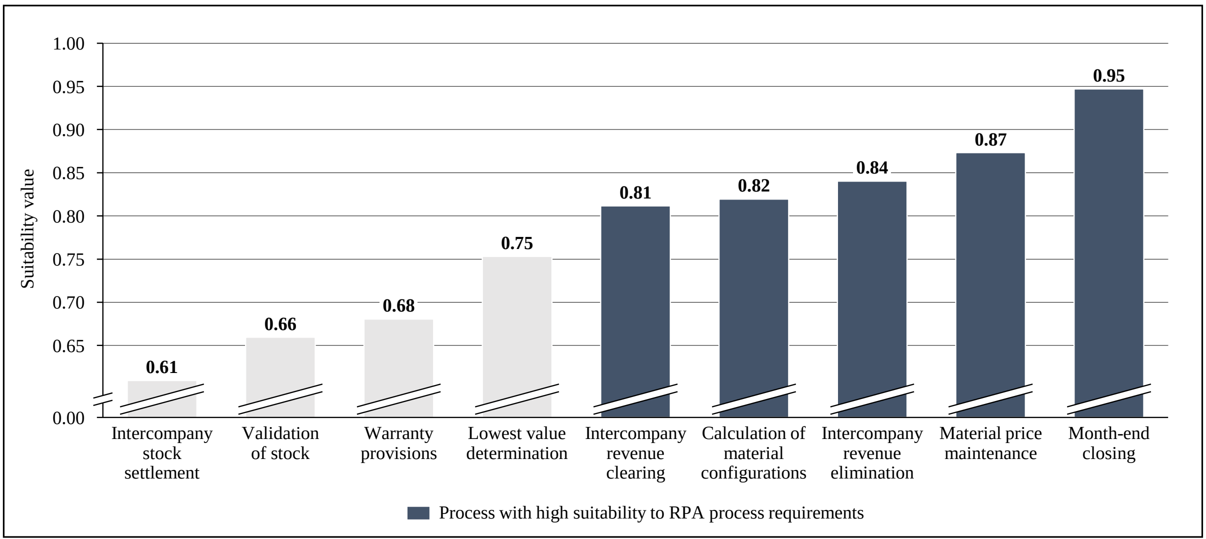

Figure 2.2: Examined processes and suitability values.

The next step was to determine the automation potential of each process by computing its suitability value. We discussed the processes with RPA experts from the company to obtain a second opinion based on their experience and internal selection procedures. As can be seen from the results in Figure 2.2, the model reveals a significant variation in the automation potential of the company's processes. The model gives suitability values ranging from 0.61 to 0.95 and presents guidance for RPA process candidates with values above 0.81. In particular, the two most significant selection criteria of standardisation and volume display great deviations and thus exert the strongest impact owing to their high eigenvectors. For volume, a threshold value of 0.3 full-time equivalents was incorporated into the s-curve formula according to the company requirements. In contrast to this, the suitability values for manual effort, maturity, digital and structured data input, and failure rate were comparable and of a high level. All results were in line with the judgement of the RPA experts.

The technical evaluation showed that the proposed model produced meaningful results and can be regarded as a reasonable basis for process selection. It provided an objective assessment of how well-suited the processes are to RPA and is able to serve as basis for decision making. The results supported the subsequent financial analysis conducted by the company (Step 3). They also confirmed the importance of identifying qualified processes according to their suitability value, because this value contains measures that determine economic viability. However, two points of criticism emerged during the assessment. First, data collection is time consuming. As long as the process is not suitable for process mining or no user interaction data are available, it also will remain cumbersome. Second, a general threshold was needed, to serve as an indicator for process selection. Judging from the case data, 0.81 might serve as a first indicator, as processes below the threshold did not meet RPA requirements in the examined case.

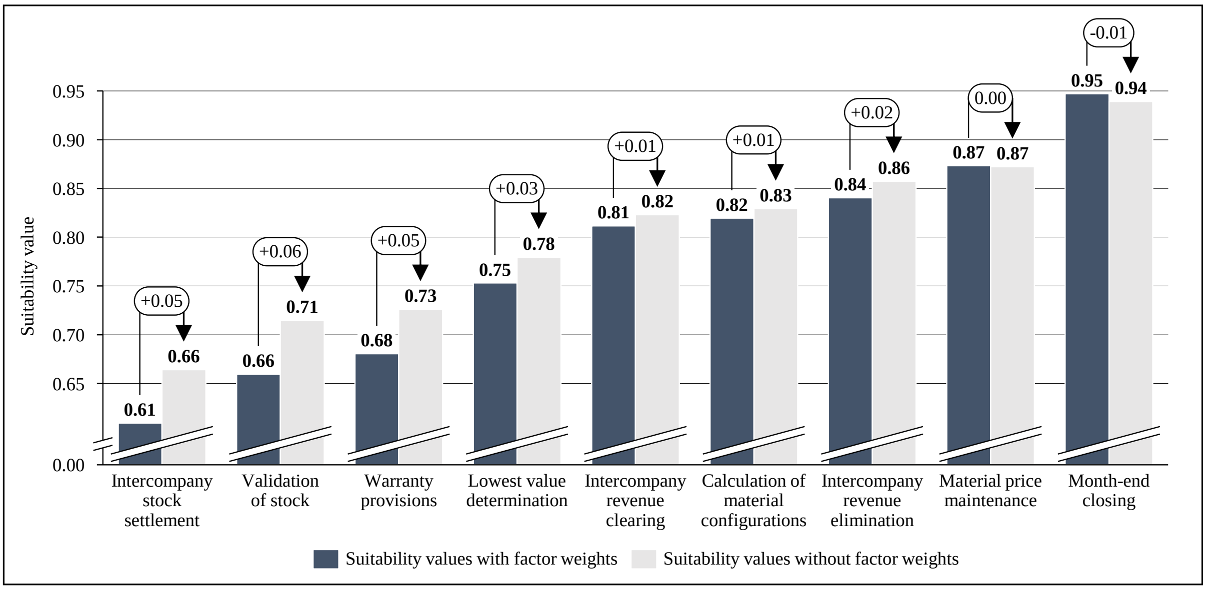

FIGURE 2.3: Sensitivity analysis of examined processes and suitability values.

To assess the model's sensitivity regarding the variation of factor weights, we conducted a sensitivity analysis and compared the results of the empirically collected factor weights with a uniform distribution. Therefore, we set all seven factor weights to a value of 0.14 which weakens the two strongest criteria standardisation (-0.09) and volume (-0.03) and slightly strengthens the impact of proneness to changes (+0.01), digital (+0.02) and high-quality (+0.03) data input and high failure rate (+0.03). The analysis revealed that even with uniform suitability values the results and the ranking of the processes did not change (cf. Figure 2.3). The findings confirmed that the proposed quantified suitability values for each process selection criterion provide meaningful results. However, processes with low suitability for automation with RPA were overrated due to the missing factor weights. The application of the empirically collected factor weights emphasised the most suitable process candidates and clearly distinguished them from unsuitable processes. Moreover, reinforcing standardisation and volume helped to identify process candidates with high economic feasibility and low implementation effort.

2.7 Conclusion, Limitations and Future Research

Over the last few years, RPA has grown into a significant technology that complements the existing BPM tool kit and widens the automation potential of company processes that previously did not justify the use of IT resources. Research shows that one of the most crucial challenges in unlocking RPA's full potential is to identify the most suitable process candidates, since the automation of unsuitable processes drives failure speed and threatens the success of a company's RPA initiatives.

In this paper, we present a systematic and generalisable method for identifying and prioritising RPA process candidates based on objective and weighted process selection criteria. To address the research question, we utilise the principles of design science research (Hevner et al., 2004, Peffers et al., 2007) and derive factor weights based on an extensive literature review, expert interviews, and a survey of 134 RPA experts. We present a three-step approach for process selection, starting with defining the goal of automation and followed by identifying and prioritising the process, and finally selecting the process by which to choose the most promising candidates for implementation. To quantify the suitability of the processes, we introduce a mathematical model to formalise the criteria and assess their impact based on empirically derived factor weights. The results demonstrate that a high degree of standardisation is the most important RPA process selection criterion and is significant at a 1% level compared to all other criteria. Standardisation is followed by a high volume of transactions, a high maturity of processes and applications, a high degree of manual effort, digital and high-quality data input, and a high failure rate. To assess the applicability of the model, it was tested with real-life case data from nine management accounting processes and refined in two iterations with operational and RPA experts. The evaluation confirms its applicability.

To our knowledge, this paper presents the first method for identifying RPA process candidates based on both weighted factors derived from empirical data and on an objective and formalised description of the degree of alignment between the process and the criteria. The results confirm the criteria proposed by existing research and case studies, which, however, were applied without assessing their importance and lacked structured selection approaches. Moreover, the reference selection criteria as proposed by Wanner et al. (2019) are confirmed and extended by digital and high quality data input. The paper also yields important practical implications for corporate executives by providing a universal selection approach along with reliable indicators. Specifically, the quantification of the process suitability can guide executives towards selecting the most promising process candidates, thereby increasing the overall probability of an RPA project's success.

The model is subject to several limitations. First, the importance of preselected criteria was derived without considering application scenarios. Potential differences in the perceived importance of process selection criteria depending on use cases and motivation are neglected. Second, the proposed model assesses process candidates based on their status quo and does not account for potential improvements prior to automation with RPA that could impact their suitability. Third, a broad knowledge of each process and a large amount of input data is required to run the model. Unless the data are available in a standardised and structured form, it could be subject to human judgement and lack reliability and comparability. Both the predefined guidelines introduced for all process characteristics and the structured data collection process can help to overcome this. Fourth, the proposed model does not include an explicit economic assessment of the processes, because criteria such as volume or standardisation are already an indication of economic viability. In addition, the utilisation of economic indicators depends on various implementation scenarios and relies on corporate standards, which is why they are not explicitly incorporated. Fifth, the factors are not independent of each other and can potentially affect one another.

Future research opportunities arise from both the limitations and the dynamic development of research in the field of RPA. In general, we encourage future research to examine automation potential with RPA in various industries and corporate functions. This can also serve as a means of testing and further refining the model. Moreover, combining data collection and process identification with innovative approaches and technologies constitutes an interesting field of research. For example, process mining or natural language processing can be used to overcome the need for manual data collection and thus enable continuous process discovery. Research indicates that by leveraging technologies such as optical character recognition or machine learning, RPA is becoming more intelligent (Plattfaut, 2019, Syed et al., 2020, Viehhauser, 2020). We therefore encourage future research to further examine the impact of intelligent technologies on the applicability of RPA with regard to the importance of process selection criteria and factor weights. The findings from our interviews indicate that the need for standardisation, maturity, and structured data input could potentially be affected. Moreover, the integration of an economic assessment into the mathematical model could be of interest, depending on the motivation for automation. Finally, examining upstream and downstream methodologies for the proposed prioritisation model may also be of interest (e.g. Santos et al., 2019). On the upstream stage, there is a lack of research into the degree of organisational readiness for RPA as well as about the resources and processes required to prepare for an effective RPA implementation. On the downstream stage, research into methodologies and technical considerations to improve the implementation phase, for instance using agile methods, may also be of interest.

3 | RPA and Management Accounting: A Multiple Case Study

Abstract

Information technology has taken over companies' financial ledgers and reporting systems, and management accounting is no longer possible without it. After the implementation of enterprise resource planning and other accounting information systems, robotic process automation (RPA) has emerged in recent years as a new means of automation and provides a virtual digital workforce for the performance of management accounting tasks. However, little is known about the adoption of RPA and its implications for managerial accounting and control; this, even though management accounting appears to be promising due to its transactional nature and manual inefficiencies. Therefore, the purpose of this research is to explore the effects of RPA on management accounting tasks and techniques, as well as on the organisation and role of management accounting. This paper builds on field data from five case companies that apply RPA in their management accounting departments and utilises the institutional theory to explain management accounting change. The overall applicability and impact of RPA on management accounting change is discussed and a task classification for automation candidates is presented. The findings show that RPA is suitable for management accounting automation and increases overall routinisation. However, it is evident that RPA has only minor impact on management accounting change.

Author: Johannes Viehhauser

Status: Working Paper

3.1 Introduction

In recent years, a new technology has evolved that revolutionises the automation of administrative tasks, just as physical robots did in the production processes of manufacturing companies few decades ago: robotic process automation (RPA) (Seasongood, 2016). RPA is defined as “a preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management” (IEEE Corporate Advisory Group, 2017). For some years now, the first case studies focusing on RPA and its applicability to as well as its effects on finance tasks in accounting and auditing have emerged. Research indicates that RPA provides an effective instrument for the automation of accounting and auditing processes, as many of these are deterministic, follow clearly defined workflows and are of high volume. Moreover, it has been shown that the profile of accounting employees is affected by further development in the direction of analytical and information technology (IT) requirements and less emphasis on data handling (Cooper et al., 2019, Fernandez and Aman, 2018, Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019, Moffitt et al., 2018).

Also management accounting, which is intended to provide financial and non-financial decision-making information to corporate management, is heavily dependent on and impacted by the developments in information technologies, mainly in relation to its financial ledger and reporting systems (Quattrone, 2016). This is attributable to the fact that corporate management depends on extensive data and real-time reporting to be able to cope with complex and fast-paced business environments (Appelbaum et al., 2017). Commercial publications point out that RPA is suitable for automating management accounting processes. According to a study by PwC of 141 companies in Germany, Austria, and Switzerland, 54% of all companies already use RPA, out of which 63% automated management accounting processes (Loitz et al., 2020). However, no research on RPA and management accounting exists. This is interesting, because research emphasises that, despite the introduction of enterprise resource planning systems (ERPS) and other integrated IT solutions, management accounting is still heterogeneous with a low level of integration at many companies. Moreover, processes demand a high level of manual effort for data handling and peak workloads for month-end closing (Dechow and Mouritsen, 2005, Granlund, 2011, Rom and Rohde, 2007). RPA promises to fix these problems, since prior research shows that this technology is particularly suitable for automating repetitive, manual and transactional tasks. This seems to give some indication that management accounting is a suitable candidate for automation using RPA.

To address the research gap identified, the purpose of this research is to examine the impact of RPA on management accounting tasks and techniques, as well as on the organisation and role of management accounting. This paper builds on the history of research on ERPS and management accounting change established by Granlund and Malmi (2002) and uses it to assess the role and impact of RPA as an innovative lever for management accounting automation. It seems to be the right moment in time to conduct this research, as the application of RPA technologies is developing rapidly. Many RPA projects are still ongoing or starting, with only few companies having significant experience with RPA. Therefore, current developments can be observed and findings can be made to help better understand RPA in the context of management accounting. To address the research question, a cross-sectional multiple case study approach is used (Eisenhardt and Graebner, 2007, Yin, 1981). Five sample companies that apply RPA in their management accounting departments are studied in detail and consultant perspectives are added in order to obtain a holistic cross-company understanding. Institutional theory, as introduced by Burns and Scapens (2000), is applied to understand and clarify the forces that drive both change and continuity in management accounting. The theory provides an appropriate lens to explore the status quo and any changes occurring, as well as the ongoing interplay between actions and institutions driving the process of change itself (Burns and Scapens, 2000, Granlund and Malmi, 2002).

To ensure a structured examination of the impact of RPA on management accounting, this research conceptualises the definition of management accounting by Rom and Rohde (2007) and adapts it to the peculiarities of RPA. Management accounting is divided into the four dimensions tasks, technologies, organisation and roles, as well as organisational behaviour. First, a focus is placed on the impact of RPA on tasks, techniques, and the role and organisation of management accounting in the companies studied. The following questions are raised: What tasks are suitable for automation with RPA? How does RPA affect the management accounting tasks used? How does RPA impact applied management accounting techniques? This question is important, as it is common for the methodologies used to be subjected to evaluation after any changes to information systems are made. How are financial or non-financial performance measures affected by the implementation of RPA? To what extent does RPA lead to changes to the organisation of management accounting? How does the role of management accounting, as well as that of management accountants, change? Moreover, the motivation for change and any resulting benefits are also investigated. Secondly, the impact of RPA on the entire organisation and on management control is examined. In this way, the following questions are discussed: How does the implementation of RPA affect the overall organisation? To what extent is management control affected by automation? Does RPA enhance the centralisation of management accounting?

This research makes several noteworthy contributions to the literature and yields implications that may inform future research. In general, it extends knowledge about RPA and management accounting change and confirms the general suitability of RPA for management accounting tasks. RPA drives routinisation through automated performance as well as through increased standardisation of tasks. However, the companies examined reveal that only a small number of tasks has been automated to date. Therefore, it is shown that management accounting and the tasks of management accountants are only slightly changed by the implementation of RPA. To guide the selection of management accounting tasks for automation with RPA, generally valid task categories based on six fields of application are proposed. In addition, an analysis framework to assess the impact of RPA on management accounting change is presented. The results inform managerial practice and guide corporate executives to further expand RPA in management accounting. Moreover, the role changes of management accountants identified help with the adaption of the training and hiring criteria for management accountants.

The paper is organised as follows. In the next section, existing literature streams on management accounting as well as on RPA are discussed. In the section after that, a detailed overview of research methodology, the case studies conducted and the process of data collection and analysis is given. Moreover, a framework for the assessment of management accounting change is introduced. In the central section that follows on, key results of the case studies examined are described and analysed through the lens of institutional theory. After a discussion of key results, the paper ends with a conclusion that considers the potential limitations resulting from the applied method and the case companies studied as well as derived ideas for future research.

3.2 Theoretical Development

3.2.1 The Role of Information Technology in Management Accounting

The goal of management accounting is to provide managers with both financial and non-financial accounting information for decision-making (Appelbaum et al., 2017). However, research indicates that, in recent decades, the focus of management accounting has changed and has developed away from backward-looking control purposes based on historical values to forward-looking strategic planning, control, and decision making (Granlund and Malmi, 2002, Rom and Rohde, 2007, Taipaleenmäki and Ikäheimo, 2013). Historically, management accounting was organised as a centralised department and performed solely by management accountants, who were in charge of management information. These accountants' roles were narrow and more or less followed a 'bean counter' role model. This fixed, narrow focus was adequate, because the business environment was somewhat stable and involved limited organisational complexity and restricted competitive environments. Moreover, managers focused on annual controls and based their decisions to a large extent on historical information (Rom and Rohde, 2007, Taipaleenmäki and Ikäheimo, 2013). In contrast, there is a consensus within the literature that both work itself and the role of modern management accounting has changed. Management accounting has developed into a more strategic approach with greater business-orientation and a focus on the identification, measurement and management of the financial and operational drivers of shareholder value (Appelbaum et al., 2017, Burns and Baldvinsdottir, 2005, Ittner and Larcker, 2001). At the same time, the literature reveals that the traditional view of management accounting as being at the core of organisational information systems changed. Boundaries are fluid, since accounting knowledge spreads outwards within organisations and is accessible to both management accountants and general managers (Burns and Baldvinsdottir, 2005, Caglio, 2003, Rom and Rohde, 2007). The role of management accountants has become broader. Management accountants have now grown into more of a business partner role, with less data gathering and number crunching and more interpretation, strategic decision-making and consulting (Byrne and Pierce, 2007, Caglio, 2003). According to the existing literature, this change to management accounting constitutes more of an evolutionary than a revolutionary process, whereby practice in this area has been characterised as slow to change (Burns and Scapens, 2000, Granlund and Malmi, 2002, Scapens and Jazayeri, 2003). An explanation for such stability can be found in economic terms, since changes in management accounting only infrequently result in significant net benefits to an organisation. Another explanation consists of the routine nature of management accounting, which reflects institutionalised practices that are themselves slow to change and often face resistance (Burns and Scapens, 2000, Granlund and Malmi, 2002).

Changes to both management accounting and to the roles of management accountants tend to be brought about by various exogenous and endogenous factors. Exogenous causes for change can be found, for example, in changing market conditions and increasingly competitive market environments (Burns and Baldvinsdottir, 2005, Burns and Scapens, 2000, Byrne and Pierce, 2007). In contrast, most changes to management accounting are driven by endogenous factors, such as organisational re-design, innovations in managerial philosophies or techniques, and growing business complexities, which require more timely and relevant data. Research has put particular focus on technological developments and information technologies as transformative forces for management accounting change, since management accounting heavily relies on the availability and analysis of large volumes of data (e.g. Burns and Baldvinsdottir, 2005, Granlund and Malmi, 2002, Scapens and Jazayeri, 2003).

A central stream within the research on management accounting and information technologies deals with the implementation and application of accounting information systems and their impact on management accounting. Accounting information systems range from simple spreadsheet solutions and specialised software to integrated information systems, such as ERPS (e.g. Granlund and Malmi, 2002, Rom and Rohde, 2007, Taipaleenmäki and Ikäheimo, 2013). ERPS integrate all flows of financial and non-financial information within organisations and constitute the basis for the management and coordination of resources, information, and functions (Granlund and Malmi, 2002). Its connection to management accounting is important, since the implementation of new information systems can cause changes to company-wide processes as well as to the overall logic governing accounting practices. Moreover, ERPS provide fast and easy access to data, although this data still needs to be translated by management accounting into relevant information before being released.

A number of academic articles investigate the impact of ERPS on different dimensions of management accounting. For example, Granlund and Malmi (2002) and Scapens and Jazayeri (2003) analyse the implications on management accounting tasks and techniques, Byrne and Pierce (2007), Caglio (2003) and Goretzki et al. (2013) investigate the changing role of management accountants, while Quattrone and Hopper (2005) or Järvenpää (2007) focus on the organisation of management accounting. Granlund and Malmi (2002) and Scapens and Jazayeri (2003) laid the foundation for subsequent studies into the impact of ERPS on management accounting and the roles of management accountants. Based on an early exploratory field study involving ten companies, Granlund and Malmi (2002) concluded that ERPS has only a moderate impact on management accounting. According to their findings, management accounting techniques did not change with the introduction of ERPS and both methods and controls showed only minor changes. Companies simply transferred their existing principles into the new integrated system without any alterations. An additional explanation is to be found in the stabilising role of ERPS, which reinforced management accounting routines. What changed, however, was inception of more rapid, easier access to standardised operational data, which reduced the number of routine tasks and allowed more time for analyses. In a longitudinal case study of a large multinational company, Scapens and Jazayeri (2003) confirmed that computerisation via ERPS drove the routinisation of management accounting, broadened the role of management accountants and, in so doing, increased overall available capacity. They saw management accounting as consisting of organisational routines and concluded that integration, standardisation, routinisation and centralisation were all drivers of change in this area. As with Granlund and Malmi (2002), management accounting techniques were not impacted significantly.

In a more recent study, Sánchez-Rodríguez and Spraakman (2012) analysed the implications of ERPS on performance measures, management accounting techniques and activities, and the use of non-financial information. They found that management accounting techniques changed due to the expansion and further standardisation of charts of accounts, together with extensive transactional records and performance measures. Moreover, they concluded that general access to and utilisation of non-financial information increased. Sánchez-Rodríguez and Spraakman (2012) also added to findings relating to increased routinisation. They determined that management accountants need to become more IT savvy, since they are involved in the operation, design and implementation of IT systems. Compared to Granlund and Malmi (2002) and Scapens and Jazayeri (2003), who all mainly orientated their analyses towards an information perspective, Sánchez-Rodríguez and Spraakman (2012) introduced physical and transactional dimensions as a way of analysing both management accounting and ERPS. The greater impact here can potentially also be explained by the advanced use of ERPS, which was not yet fully available in earlier studies. It seems clear that it is important to analyse management accounting in terms of all three dimensions, since, for example, improved transaction processing via ERPS is only possible with optimised and standardised physical processes.

Caglio (2003) conducted an important case study to examine the impact of ERPS on the management accounting profession. This showed that the introduction of ERPS increased the mobility and transferability of management accounting tools and techniques and thereby removed some of the existing boundaries between activities within organisations. ERPS changed management accounting activities and responsibilities and led to new hybrid positions of management accountants by adding such things as IT maintenance and business consulting tasks to traditional management accounting roles.

Besides the conversation on the impact of integrated information systems on management accounting, another recent research stream focuses on business intelligence and analytics. These technologies ease data collection, analysis and supply of information and in this way, assist reporting and decision-making. Because the support for decision-making in organisations is an essential activity of management accounting, there is a clear link to the technology (Appelbaum et al., 2017, Rikhardsson and Yigitbasioglu, 2018). However, Appelbaum et al. (2017) conclude that most organisations still mainly utilise descriptive analytics, whereas predictive and prescriptive analytics, which are the principal advantages of business intelligence and analytics technologies, are barely used.

Overall, it becomes evident that technological developments and especially information technologies are an important transformative force that drive change in management accounting. As integrated information systems impact management accounting and particularly the role of management accountants, the question arises whether RPA, as a digital imitation of management accountants, changes the discipline even further. Moreover, because the development and integration of integrated information systems is both costly and complex, many organisations still suffer from manual processes and the existence of necessary interfaces between systems. Building on existing infrastructure with no need for adaption, RPA could leverage the adoption of more automation and changes management accounting. To explore the potential implications for management accounting, it is important to know the impact of existing systems, as described above. For this reason, this paper is based on the findings and proven methodologies of research into management accounting change and the various forms of information technologies.

3.2.2 Robotic Process Automation as a Lever for Change

As introduced in Section 3.1, RPA comprises licensable software functioning as a 'virtual workforce' that carries out computerised business processes and works in the same way that humans do (Lacity and Willcocks, 2016, Plattfaut, 2019, van der Aalst et al., 2018). The software simulates both keystrokes and mouse controls and is integrated into the user interface, which makes access to software back end and expensive application interfaces superfluous (Asatiani and Penttinen, 2016). The operation of RPA on user interfaces provides considerable ease of use for non-programmers, thereby enabling rapid, problem-free implementation. From a technical perspective, RPA can be classified into attended robots, which work on the computer of and in close interaction with users, and unattended robots, which work in the back-end on central servers or in clouds (Lacity and Willcocks, 2016). RPA forms part of the broader discipline of business process management. Business process management solutions, such as integrated information systems, are fully integrated transaction systems that are driven by IT professionals and require significant investments. According to Bygstad (2017), they are referred to as 'heavyweight IT'. In comparison, RPA is regarded as 'lightweight IT' and is complementary to heavyweight solutions, since both of these address different types of processes (Bygstad, 2017, van der Aalst et al., 2018). The added value of RPA is illustrated by the 'long tail of work' (cf. Figure 1.1), which shows a Pareto distribution of business processes. Processes with high case frequencies are typical candidates for heavyweight solutions and account for around 80% of all cases (van der Aalst et al., 2018). In the context of management accounting, integrated information systems cover these processes. The remaining around 20% of cases or 80% of processes do not justify automation with heavyweight IT, as it is just not economically viable to develop heavyweight IT solutions for them. By applying RPA, the large and time-consuming central part of the 'long tail of work' involving processes that comprise smaller volumes can be automated (van der Aalst et al., 2018). Research has broadly examined process characteristics best suited to the efficient deployment of RPA. Processes should be repetitive, standardised, follow clearly defined rules with little need for human judgement and few exceptions, should be mature, and should have both digital and structured data input (e.g. Lacity and Willcocks, 2016, van der Aalst et al., 2018, Wanner et al., 2019). As a result, one of the core advantages of RPA is an increase in the efficiency and effectiveness of process performance, which results in personnel savings and released personnel capacities. Moreover, the quality of services, accurateness of outputs, and speed of execution can be increased. In this way, time-critical tasks in particular, such as month-end closing or reporting, can be performed, so as to reduce bottlenecks. In addition, compliance is increased, while the logs of all activities are available for documentation or process improvement (e.g. Hallikainen et al., 2018, Lacity and Willcocks, 2016, Plattfaut, 2019).

Research on RPA is comparatively rare and at an early stage. Most articles are based on case studies and address general problems of deploying and organising RPA or identifying suitable processes in various industries or functions. With regard to the use of RPA with finance tasks, initial research with focus on RPA in accounting or auditing is currently evolving, as these functions are characterised by a large number of rule-based and high-volume processes. Cooper et al. (2019) conducted a case study of 14 accounting companies to examine the use of RPA in public accounting. The authors concluded that RPA had great potential for use with tax services, such as compliance and reporting tasks. RPA increased the accuracy of work, improved processing times by up to 80% and reduced the demand for human labour at the case companies examined by over one million work hours in 2017. Moreover, the qualification profile of accountants changed, with there being greater need for programming experience and more emphasis on both accounting knowledge and analytical skills.

Based on a case study into accounting and finance functions in multiple industries, Kokina and Blanchette (2019) confirmed the changes to the job profiles of accountants, with there being more focus on analytical and IT skills, such as RPA development, testing, and support. In addition, they concluded that business process management now plays a more prominent role. The authors observed that accounting tasks within the order-to-cash and procure-to-pay process, such as payment, invoicing, or supplier and customer master data management, offer promising opportunities for RPA. These are repetitive, follow clear rules, operate in multiple systems and rely on structured data. RPA also impacts global accounting service providers, both on an individual as well as organisational level, as shown through an in-depth case study by Fernandez and Aman (2018). The research confirms the changes to the work of accountants as described above and shows that RPA reduces the need for accountants significantly. Another research stream examines the impact of RPA on auditing (Huang and Vasarhelyi, 2019, Moffitt et al., 2018). The authors confirm that auditing tasks are also suitable candidates for automation with RPA, since many of them are deterministic, repetitive and follow predefined workflows. Automation with RPA resulted in the elimination of repetitive and non-value-adding tasks, unleashed additional processing power, increased the accuracy of both outcomes and services, and secured auditability and reliability.

The review of the literature shows that RPA is an effective instrument for the automation of finance processes and tasks. Especially repetitive, high-volume, and rule-based processes, which are widespread in finance functions, are suitable candidates for automation. Therefore, RPA expands further the degree of automation that can be used, beyond integrated information systems and business intelligence solutions. However, to date, no research is available that addresses the use and effects of RPA in relation to management accounting; this, even though RPA seems promising for management accounting, since it still comprises many system interfaces, spreadsheet solutions, and a high degree of time-critical, manual, and repetitive tasks. This clearly underlines the need for more research into RPA and management accounting.

3.3 Research Methodology

3.3.1 Applied Methodology and Context of Research

To examine the impact of RPA on management accounting, a cross-sectional multiple case study approach is used (Eisenhardt and Graebner, 2007, Yin, 1981). This approach is applied broadly in management accounting research to examine the forces driving change. It enables a comprehensive understanding to be gained, offering rich explanations for new phenomena, such as RPA and management accounting, which lack an established theoretical foundation. At the same time, case-based research has been widely adapted in the information systems domain, in order to assess newly emerging technologies in organisations (e.g. Byrne and Pierce, 2007, Conboy et al., 2012, Granlund and Malmi, 2002, Orlikowski and Baroudi, 1991).

This research is contextualised within established European non-tech companies, drawn from various industries and with global operations. The companies operate at different stages of the value chain. This is important to the investigation of RPA, since a company's position within the value chain can affect the degree of integration of applied systems. For example, suppliers with multiple customers need to develop interfaces to customers' systems or even take over their IT applications. In this way, the degree of system integration is reduced. In contrast, downstream companies can operate highly integrated information systems, since they exert a certain degree of power over their suppliers. Moreover, the case companies are of different sizes. Corporate size is used as approximation for the professionalism and capacity of the accounting systems used. Smaller companies often face disintegrated system landscapes, with various stand-alone solutions or proprietary systems developed outside leading integrated information systems. With regard to RPA, all case companies have installed RPA technologies within their organisations and practice an advanced stage of use. To control for this variable, the stage of adoption of RPA within the entire organisation, as well as within the management accounting department, is identified systematically and discussed. The focus is a narrow one – on a particular point in time. On the one hand, RPA implementation is at an early stage and historical data for a longitudinal study is absent. On the other, the study addresses the resulting impact of RPA on management accounting and not the relevant driving forces.

3.3.2 Case Selection and Data Sources

The case studies were selected based on purposeful sampling, with the goal being to include information-rich cases that cover various perspectives of the criteria introduced in Section 3.3.1. In total, five companies were identified in the course of discussions with leading RPA software providers, as well as through public available information, such as panel discussions and press releases. All companies have successfully set up RPA within their organisations and have managed to automate management accounting tasks at various stages. The case selection process revealed that many companies started to utilise RPA, mainly in their accounting, purchasing, and human resources functions. With regard to management accounting, it has been shown that the implementation of RPA is still at an early stage and only few companies have established RPA on a large scale. This finding emphasises that it seems to be a good moment to initiate research into RPA and management accounting. Below is an overview of the five case companies:

- Company A: a multinational chemicals company with annual revenues of more than EUR 23 billion, around 80 thousand employees, and more than 100 establishments globally. This company established a global RPA centre of excellence and automated more than 140 processes in finance, human resources, legal, tax and operations, amounting to over 100 full-time employees in terms of savings.
- Company B: an international logistics service-provider with annual revenues of over EUR 1.0 billion, around 17,000 employees, and over 70 corporate locations. This company established an RPA centre of excellence for its global operations with three employees in 2019 and automated major processes using RPA across all functions and business units.

- Company C: an international semiconductor manufacturer with annual revenues of EUR 8 billion, over 41,000 employees across four business units and 130 establishments globally. This company established an RPA centre of excellence in 2019 and rolled out RPA to major processes across various functions. However, management accounting is still at an early stage with regard to RPA usage.

- Company D: a multinational chemicals company with annual revenues of over EUR 5 billion, around 15,000 employees organised along four business segments, and over 25 establishments globally. This company started its RPA journey in 2018 and organised RPA centrally within its process management department. The technology is rolled out company-wide and various processes across all functions and business units are currently in the course of being automated.

- Company E: a sports equipment manufacturing company with revenues of around EUR 200 million and 2,000 employees globally. The company started its RPA journey in 2020 and is still at an early stage, with automation involving initial robot trials within their management accounting and marketing functions. The RPA initiatives form part of a process optimisation unit, which in turn is a sub-division of the corporate IT department and they are managed centrally.

Semi-structured interviews were used as the primary source of data. To obtain insights and experiences from various angles and to increase validity, interviews with RPA experts and management accountants were conducted for each case company (cf. Table 3.1). The former aimed to contribute technical perspectives, such as process selection criteria, technical peculiarities, or implementation efforts. The latter aimed to contribute management accounting specific perspectives about, for example, the usability of RPA and its impact on accounting techniques and tasks, changes in the organisation, or impacts on management control. The involvement of interviewees from various hierarchical levels and functional areas helped to overcome a potential elite bias. Additional interviews with RPA consultants were included to obtain cross-company insights with experiences on RPA and management accounting from various customers. They also introduced knowledge about the latest technical RPA capabilities. In this way, potential shortcomings of the purposeful sampling can be controlled. In addition to the interviews, process documentation and other records were collected and analysed in the course of the research.

Table 3.1: Overview of conducted interviews and interview participants.

Company	Company type	Position of interview partner	Origin
Company A	Chemicals company	Executive Director Digital Business Services Finance Manager Operations	Germany United Kingdom
Company B	Logistics service provider	Head of Competence Centre RPA Head of Group Controlling	Germany Germany
Company C	Semiconductor manufacturer	Head of RPA Centre of Excellence Manager Accounting Processes and Projects	Portugal Germany
Company D	Chemicals company	Head of RPA Centre of Excellence Management Accountant	Germany Germany
Company E	Sports equipment manufacturer	Head of IT Management Accountant	Austria Austria
Consultant A	RPA consulting company	Senior RPA Consulting Manager	Spain
Consultant B	Strategy consulting company	Principal Corporate Performance	Austria
Consultant C	Strategy consulting company	Project Manager Financial Services	Germany

The interviews were structured into three parts. First, general information about the RPA organisation as well as the maturity of RPA implementation was discussed. In this context, a detailed overview of the project was given and anonymity was granted, in order to overcome any lack of trust. Second, all automated management accounting processes, their identification, the resulting benefits and any challenges cropping up were enquired about in detail. Third, the potential implications for management accounting as well as for management control were discussed (cf. Table A.4). The interviews lasted between 45 and 70 minutes and were conducted via phone or video calls. All interviews were transcribed and then sent out for review, in order to avoid mistakes or misunderstandings. Interviewing techniques, such as non-direct speech and open questions, were used so as to receive accurate information. During the analysis process, follow-up calls were conducted, if required, in order to clarify any missing or unclear information.

3.3.3 Data Analysis and Conceptualisation of Management Accounting

For data analysis purposes, all empirical data was coded using MAXQDA, which enabled detailed word-by-word coding. The analysis consisted of two phases. In the first phase, a case-based analysis of the data collected was conducted, in order to obtain a detailed understanding of the peculiarities of the RPA initiatives and their impact on the management accounting practices of each of the five companies. Moving back and forth between the empirical data, theory and previous research helped to develop a detailed understanding of the empirical data itself and also to understand what occurred within the firms. In the second phase, a cross-case analysis of all five companies followed on as a way of identifying emergent patterns and refining and condensing the findings into categories.

To ensure a structured examination of the impact of RPA on management accounting, the analysis builds on the definition and conceptualisation of management accounting by Rom and Rohde (2007), which is adapted to the peculiarities of research on RPA (cf. Figure 3.1). The authors divide management accounting into the four dimensions: tasks, technologies, organisation and roles, as well as organisational behaviour. The theoretical framework is intended to guide research on management accounting and integrated information systems and is broadly applied, in order to assess the impact of technology on all four elements of management accounting (e.g. Lukka, 2007, Rikhardsson and Yigitbasioglu, 2018). It is not limited to research on integrated information systems and is also used, for example, in the context of business intelligence and its implications for management accounting (Rikhardsson and Yigitbasioglu, 2018). Therefore, it provides a proven and reliable theoretical foundation for research on RPA. The relation between RPA and management accounting is regarded as bidirectional. Even though RPA as technology is not changeable, each process is individually designed during the implementation phase and subject to continuous adaptions and further developments during operations. In the context of this early research, a focus is placed on the effects of RPA on management accounting and any contrary implications are ignored. Moreover, the analysis incorporates the conceptual model by Santos et al. (2019). Based on a review of the literature on evolving research on RPA, the authors propose to conduct case study research on RPA, focusing on the dimensions of strategic goals, process analysis and tactical evaluation. Thus, it can be ensured that all aspects of RPA automation and resulting impacts are considered.

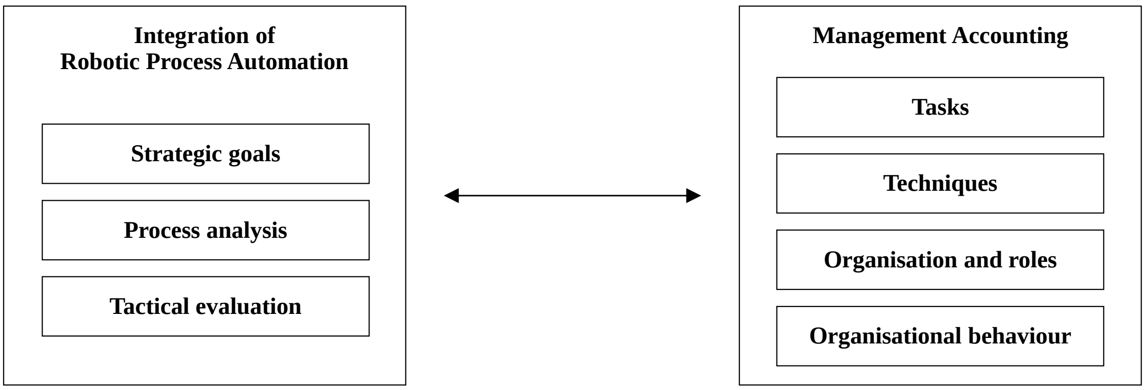

Figure 3.1: Theoretical framework for research on RPA and management accounting.

Management accounting tasks are defined as the 'doing' of management accounting and comprise tasks such as business planning, transaction processing, performance measurement, reporting and control and decision-making support (Rom and Rohde, 2007). The existing research on the impact of integrated information systems reveals that the tasks carried out by management accountants tend to become less transactional, with less data-gathering, data input and consolidation workload. In turn, these tasks become more wide-ranging, develop more of an analytical, business partner role, while management accountants require new skills and knowledge about process improvement or IT (Granlund and Malmi, 2002, Lodh and Gaffikin, 2003, Sánchez-Rodríguez and Spraakman, 2012). As research on RPA emphasises that technology reduces routine, transactional tasks that tend to be error-prone, I hypothesise that RPA could potentially impact management accounting tasks by eliminating even more repetitive, manual work as well as by increasing the need for IT and process knowledge.

Management accounting techniques constitute the second dimension of the framework and are used to achieve the goals of management accounting by being made to perform accounting tasks. Examples of such techniques include zero-based budgeting, forecasting, activity-based costing, cost and profitability allocation and the balanced scorecard method (Rom and Rohde, 2007). The framework distinguishes between techniques and outcomes as a basis for actions. Early research on integrated information systems gives rise to the conclusion that techniques are not impacted by leveraging technologies. Existing techniques are being transferred into the systems without changes to their logic. However, the degree of standardisation, availability, speed of execution and accuracy increases, while additional analyses are also possible (Granlund and Malmi, 2002, Scapens and Jazayeri, 2003). In more recent research, Sánchez-Rodríguez and Spraakman (2012) build on these findings by identifying that techniques change with a more extensive, standardised chart of accounts. Standardisation is achieved through increased integration and inter-departmental collaboration. With regard to outcomes, it was shown that access to both financial and non-financial data was simplified, thereby resulting in more extensive, more detailed and more frequent performance measuring (Granlund and Malmi, 2002, Sánchez-Rodríguez and Spraakman, 2012). Since research indicates that, in particular, reporting, consolidation and budgeting techniques are still performed in multiple independent systems and spreadsheets, I hypothesise that RPA might have an impact on management accounting via these techniques. Moreover, availability, efficiency and effectiveness could potentially be improved further.

The organisation of management accounting functions as well as the role of management accountants form the third pillar of the analytical framework (Rom and Rohde, 2007). Research reveals that the introduction of ERPS increases the centralisation of data processing, demands dedicated IT knowledge as well as stronger interfaces to the IT department and reduces the overall size of management accounting functions. Management accountants evolve into broader business-orientated roles with inter-departmental responsibilities (Caglio, 2003, Granlund and Malmi, 2002, Sánchez-Rodríguez and Spraakman, 2012). I hypothesise that the utilisation of RPA strengthens the changes described by placing even more emphasis on analysis and business-sense, increases the need for IT knowledge as well as overall process improvement; and it potentially reduces further the size of management accounting departments.

Finally, the impact of management accounting on organisational behaviour as well as on the organisation's perception of management accounting is examined (Rom and Rohde, 2007). According to Granlund and Malmi (2002), the implementation of new technologies drives changes in control as well as accountability levels and affects business process re-engineering. Spathis and Ananiadis (2005) add that ERPS also lead to improved decision-making by decentralising the availability of information. I hypothesise that RPA could potentially reinforce these effects.

In addition to the four dimensions of management accounting, Rom and Rohde (2007) also propose to assess the implications for corporate performance, for example, in relation to the share price, as an outcome variable pertaining to integrated information systems. Since this paper addresses the applicability and the resulting benefits of RPA in the context of management accounting, it is not expedient to assess the effects on overall performance impacts. For this reason, performance is defined as efficiency gains and the resulting effect on the costs limited to the management accounting sphere. These are considered as part of the 'organisations and roles' dimension of the framework.

To clarify the forces that drive change and continuity in management accounting, the institutional theory and the conceptualisation of management accounting change devised by Burns and Scapens (2000) are applied. As described in Section 3.2.1, management accounting is regarded as stable and slow-to-change. This stability can be explained by the routine, institutional nature of management accounting, with practices that amount to stable organisational rules and routines. Moreover, accounting systems are designed to meet long-term requirements and to enable control in an unstable and changing ecosystem, which is why they themselves are also comparatively stable. For this reason, institutional theory constitutes an appropriate lens for understanding and explaining the changes in, and stability of, management accounting (Burns and Scapens, 2000, Granlund and Malmi, 2002). The theory conceptualises change as the interplay between the institutional realm, with its rules, routines, and the realm of action. For example, formal management accounting systems constitute rules, whereas the accounting practices actually in use constitute routines. In this way, the status quo and any changes occurring can be explored in terms of the ongoing interplay between actions and institutions that drive forward the process of change.

3.4 Empirical Results

3.4.1 Management Accounting Tasks

3.4.1.1 Impact of RPA on Management Accounting Tasks

As described in Section 3.2.2, RPA can be used to automate rule-based and repetitive tasks with structured digital data input. The findings of all companies studied suggest that management accounting provides various tasks suitable for automation with RPA. First, all of the management accounting departments examined appear to carry out a lot of manual and repetitive 'number crunching' tasks, such as data collection, data handling and data manipulation. Many of these tasks are based on clearly defined rules and are therefore well-suited to RPA. Second, the respondents emphasise the absence of standardised processes and fragmented system landscapes. Many processes have grown up historically and are inefficient, lack documentation and vary across divisions and country units. Even though all companies operate ERPS, they tend to lack integration, since not all business units and country divisions are connected, other operational or client systems, which have no interfaces, exist and tasks are often performed outside ERPS. RPA consultant B elaborates that the lack of integration is driven mainly by high costs and complexity:

> *In an ideal world, we wouldn't need RPA, as all data would be integrated into the leading information system as single source of truth. However, this is not feasible, because it is too costly, has grown up historically and is overly complex. Moreover, the systems involved are slow to change, which is why additional, more flexible solutions are needed.*

This lack of integration leads to considerable transactional effort in management accounting, as data from multiple systems need to be collected and processed. Existing research confirms that tasks with a transactional nature are well suited to automation with RPA (Syed et al., 2020). Third, the cases examined show that management accounting provides mainly low-volume tasks for automation with RPA. They lack adequate volume and are not feasible for heavyweight IT, which makes RPA a suitable solution to further increase the degree of automation. Fourth, management accounting is characterised by a peak workload at month-end. Here, RPA can provide additional capacities, since RPA decouples capacities from personnel resources and operates without regard to time restrictions.

All of the case companies examined confirm that RPA is suitable for the further automation of management accounting processes, even though most implementation projects are still at an early stage. In this way, RPA complements ERPS and provides a solution for those tasks that are presently performed manually. The results obtained show that management accounting provides six fields of application for RPA; namely, data transfer, data processing, data analysis, data preparation, systems operations and data transmission and communication (cf. Table 3.2). All of the automated management accounting tasks identified are based on well-defined rules, with very few exceptions, process digital and structured data inputs and operate in one or multiple systems without the need for special interfaces. In this way, they meet requirements for the use of RPA.

Table 3.2: Classification of management accounting tasks for an automation with RPA.

Field of application of RPA	**Examples**
Data transfer	Collection and extraction of data from one or multiple sources, upload of data into systems, handling data
Data processing	Consolidation or reconciliation of data
Data analysis	Performing deviation analysis, performing validation tasks based on predefined rules
Data preparation	Extraction and creation of reports, preparation of reporting files and numbers
Systems operation	Performing bookings in ERPS, performing calculations, performing preconfigured actions in spreadsheet solutions
Data transmission and communication	Communication of data via, e.g. e-mail

Overall, the tasks of management accountants who work with RPA are becoming less transactional, with less manual data handling and data manipulation. In turn, the task profile in this area is now developing towards analysis, interpretation and development of measures enabled by the increased capacity that has come on stream. In addition, the task profile is supplemented by the use of RPA tools. Findings in this area indicate that RPA is a suitable automation solution for management accounting, but has only a minor impact on task changes. Only small parts of main processes and individual, low to medium volume tasks with savings ranging between 1 to 50 hours per month are automated. To date, none of the companies involved have implemented RPA at scale and only one to seven tasks are automated per company.

3.4.1.2 Implemented RPA Tasks in Management Accounting

Table 3.3 provides an overview of concrete examples for all management accounting tasks from the case companies examined that were automated with RPA. Operative planning and budgeting is identified as a prominent use area for RPA. For example, companies B and D apply RPA to automate transactional parts of their operative planning and budgeting process. Both companies lack a fully integrated planning system, as their budgeting process is based on multiple systems and the ERPS cannot be implemented in all business units and countries. As a solution, RPA is used to prepare planning files automatically through the extraction of actual data from ERPS, the collection and validation of data, and the consolidation of data within a central data system.

Three out of five case companies (companies B, D and E) use RPA to automate parts of their regular forecasting process. The process contains many manual and rule-based tasks, such as preparation of data collection files, steering of the data collection process, validation of data based on predefined rules and consolidation of data into leading systems. Therefore, this process has been identified as being well-suited to automation with RPA, which is also highlighted by consultants B and C and their case experience. For example, consultant B describes that RPA enabled the reduction of the monthly preparation time required to set up the rolling forecast of a large shipping company, from 16 to three days. This is because all data gathering and validation activities for data collected from multiple business units were performed by RPA. This major reduction was brought about by automation with RPA, as well as by the end-to-end streamlining of the forecasting process during the introduction of RPA. Another example looked at is the monthly revenue forecasting process of company B, for which all divisions need to update their volume and price forecasts in individual planning files for each customer and deliver them to the central management accounting unit. This data collection and preparation of consolidated revenue forecasts could be fully automated with RPA, thereby reducing lead time and enabling more rapid availability of data, together with improved quality and higher granularity.

Table 3.3: Overview of management accounting tasks automated with RPA.

Main process	Task automated with RPA	Examples
Operative planning and budgeting	Preparation of planning files	- Update of existing planning files to planning period - Pre-filling of planning files with actual data - Distribution of planning files to decentral units
	Collection and consolidation of planning data	- Tracking and collection of updated planning files - Consolidation of planning data into leading planning files or systems
	Validation of planning data	- Performance of sanity checks, e.g. missing data - Validation of planning data based on predefined rules, e.g. deviation from past values - Communication with decentral units
Forecasting	Preparation of forecast files	- Update of existing forecast files to forecast period - Pre-filling of forecast files with actual data - Distribution of planning files to decentral units
	Collection and consolidation of forecast data	- Tracking and collection of updated forecast files - Consolidation of forecast data into leading planning files or systems
	Validation and analysis of forecast data	- Performance of sanity checks, e.g. missing data - Validation of forecast data based on predefined rules, e.g. deviation from past numbers - Communication with decentral units
Cost and activity accounting and profit and loss accounting	Master data management	- Validation of master data - Collection of master data - Update of master data in systems - Communication of requests and notification about completion
	Internal cost allocation	- Collection and consolidation of performance measures from multiple systems - Consolidation and summarisation of data - Allocation of costs to internal cost centres
	Reconciliation	- Performance of rule-based reconciliations in ERPS
	Transfer pricing	- Updating transfer prices in ERPS based on manual notifications - Running mass data updates of transfer prices in ERPS (based on manual notifications)
	Deviation analyses	- Identifying deviations of actual, forecast and budget figures based on predefined rules
	Period-end closing	- Downloading actual data into reporting files for period-end closing preparation - Collection of actual data from non-integrated units - Verification of data - Uploading data into ERPS - Running journal entry posts in ERPS - Performance of period-end bookings in ERPS
Management reporting	Collection and consolidation of data	- Extraction of data from multiple sources - Consolidation of data - Uploading of data into systems or reporting spreadsheets
	Validation of data	- Performance of sanity checks, e.g. missing data - Validation of data based on predefined rules, e.g. deviation from past values
	Analysis of data	- Analysis of reporting data based on predefined rules, e.g. deviation from past numbers - Identification of causes for deviations based on predefined deep-dive analyses of detailed data
	Report generation (numbers)	- Transfer of data from systems or spreadsheets into standard reporting templates
Project controlling	Collection and upload of controlling information	- Uploading work breakdown structures and project reporting into ERPS

(continued)

TABLE 3.3: Overview of management accounting tasks automated with RPA - Continued.

Main process	Task automated with RPA	Examples
Departmental controlling	Collection and consolidation of data	- Extraction of data from multiple sources - Consolidation of data - Uploading data into systems or reporting spreadsheets
	Validation of data	- Performance of sanity checks, e.g. missing data - Validation of data based on predefined rules, e.g. deviation from past values
	Analysis of data	- Analysing data based on predefined rules, e.g. deviation from past numbers - Identification of causes for deviations based on predefined deep-dive analyses of detailed data
	Report generation (numbers)	- Transfer of data from systems or spreadsheets into standard reporting templates
	Upload of data	- Upload into databases or business intelligence tools
	Communication	- Dispatch of reports via, e.g. e-mail

All of the case companies examined use RPA for individual tasks in the areas of cost and activity accounting. They also use it in relation to profit and loss accounting and preparatory work. The maintenance of master data seems to be a promising fundamental use case for RPA, as this is repetitive and frequently involves high volumes. However, only company D uses RPA to regularly assess accounting master data, automatically request missing information and independently upload new information in ERPS. Moreover, company D also leverages RPA for entering transfer prices into ERPS and for running monthly mass updates for transfer prices. In the first case, RPA receives notifications, updates the prices in ERPS accordingly and then confirms the action. In the second case, RPA receives input files with mass data for each country and uploads this data in ERPS. As a result, around 450 employee hours could be saved annually, the response time decreased and mistakes could be avoided. The highest potential of RPA is identified as residing in the performance of period-end closing tasks. For example, RPA is used to prepare reporting files, collect actual data from non-integrated units, upload data in ERPS, run journal entry posts in ERPS and perform period-end bookings. Moreover, the technology is also used to run intercompany reconciliation tasks and to perform internal cost allocation tasks. All of the respondents examined report the use of RPA for one or more of the tasks described. For example, company B uses RPA to collect and process reporting packages from country units, which are not integrated into their ERPS. RPA pre-fills the reporting files with actual data, distributes the files to the country units, collects the data, validates the data and finally consolidates all of the information in a leading file before uploading it into ERPS. As a result, the company was able to improve data quality and to save three employee days during month-end closing, accompanied by an increase in speed of execution and availability.

The preparation of reports appears to be the most important management accounting task that can be automated with RPA. All five case companies use RPA either to prepare monthly top management reports, individual standard reports during the month or to populate business intelligence databases. For example, company B automated all of the major parts of their reporting process that were previously performed manually. First, RPA is used to collect profit and loss as well as balance sheet data from decentralised units, based on standardised reporting packages. In this way, RPA pre-fills reporting files, sends them to the managers responsible, collects the files and consolidates all the data. Second, RPA runs a detailed deviation analysis and provides specific explanations for deviations, based on predefined text elements. Finally, RPA collects data from multiple sources in a single reporting file, processes the data based on certain preconfigured actions and then automatically transfers to and visualises the data in a standard reporting document. Furthermore, company A utilises RPA to automatically prepare a daily CFO report. The technology is used to operate at night and thus makes use of non-working times. RPA collects data from different systems, prepares the data based on certain predefined actions, and then uploads the data into a central business intelligence system, which is used by the CFO in the morning. As a result, decision-relevant management information can be provided in a more timely fashion and management accountants gain additional capacities for data analysis and the drawing of conclusions.

Company C uses RPA for a data entry task in project controlling. The robot receives information from project managers concerning the amount of work, the time required, and the costs of each work package within a single spreadsheet and then inputs the information into ERPS. In this way, project managers can be relieved from manual data handling work. However, to date, none of the other companies have been using RPA for project controlling purposes.

Departmental controlling is identified as another important field of application for RPA in management accounting. The automated tasks cover data collection and consolidation, data validation and analysis, preparation of reports, communication and tracking of measures. The respondents reveal that RPA is applied to a broad range of management accounting tasks and reports, which include the controlling of departments, business units and country divisions. Examples of tasks automated with RPA include the preparation of reports for product costs, IT costs and repair and maintenance costs, the creation of key performance indicator reports for manufacturing units and the calculation of marketing and sales reports. Besides data handling and preparation, the mailing of reports and communications have also been automated with RPA. The head of the RPA centre of excellence of company D explains that, previously, management accounting lacked standardised reports and processes for departmental controlling within the management accounting department as well as for supplying data to management accounting within other departments:

> *Every business unit and country division has its own processes and standards for the preparation and reporting of information. Even though the outcomes are comparable, the execution varies significantly and is often ine cient. With RPA, we were able to establish standard processes and reports for certain information, which we could easily role out across all business units and country divisions.*

With the introduction of RPA, company D streamlined its data preparation processes and introduced standards for departmental controlling reports for various types of data. In general, all examined companies report greater decentralised efficiency and the ability to prepare additional or more detailed reports, since RPA expands available capacities. As a result, RPA makes costs more visible and also enables better costs control in decentralised departments.

3.4.2 Management Accounting Techniques

The findings suggest that RPA has no direct impact on management accounting techniques or on the methods and controls used at the case companies. Theoretical approaches, such as zero-based budgeting, forecasting mechanism or cost and profitability allocation techniques are not affected. The companies leverage RPA, in order to simply automate the execution of existing processes or principles and only adjust the relevant processes if inefficiencies crop up.

Only one company, advised by consultant B, uses RPA as an enabler to change its budgeting process and methodology. In the past, the company used static budgeting techniques with a fixed three-year time frame and no changes during the budgeting period. However, its dynamic market and business environment called for more flexible update cycles for timely management actions. To overcome this, the company introduced a quarterly rolling forecast technique. As rolling forecasts cause an increased workload in relation to collecting and rolling up data, they use RPA to perform all manual data collection and communication workflows across different systems and spreadsheet solutions, as well as for verification and processing tasks. RPA enabled processing capacities to be increased regardless of the personnel available. As a result, more frequent forecasts offering greater granularity and more rapid availability could be achieved. This finding shows that RPA can have an impact on the budgeting techniques in use, as it decouples processing requirements from processing capacities.

Financial metrics, such as performance indicators and even key performance indicators, such as outcomes of management accounting techniques, are not affected by RPA. All case companies confirm that RPA has no impact on existing metrics. On the one hand, these companies operate with established and proven metrics, which have no need for adjustments. On the other, performance indicators need to be comparable, both internally and externally, as well as steady, which makes them difficult to change. However, RPA has a direct impact on the availability of financial measures, because the preparation of data takes less time and the frequency of updates can be increased with extended capacities. By decoupling management accounting capacities from personnel resources, the granularity of key performance indicators can also be increased.

One important finding involves the direct impact of RPA on the access and utilisation of non-financial metrics, since RPA generates more non-financial information. Research reveals that the availability and use of non-financial transactional data increased with the introduction of ERPS, which facilitate access to operational data (Sánchez-Rodríguez and Spraakman, 2012). However, the case studies examined show that companies are still failing to integrate business units and country divisions, as well as various incompatible operative systems lacking useful interfaces (cf. Section 3.4.1). This impedes extensive access to non-financial information via ERPS. RPA bridges existing interfaces and manual data handling operations. In this way, it increases access to non-financial metrics on such factors as inventory, materials consumption and human resources. In the case of the logistics service provider examined, RPA sourced operative performance parameters automatically from different stand-alone systems, consolidated the information using data gleaned from the ERPS and then created non-financial metrics. The head of group controlling confirmed:

> *RPA allows us to automatically generate additional standardised non-financial key performance indicators, which we cannot compute with our ERPS due to missing integration and limited personnel resources. With RPA, we save time from manual work and can access more information with constantly high quality. This facilitates management action on a more granular level of information.*

The results demonstrate that RPA enhances performance measures with automated access to transactional and non-financial data and reinforces the effects of integrated information systems (Sánchez-Rodríguez and Spraakman, 2012). Access to both financial and non-financial metrics is more rapid and more extensive and offers a higher level of detail. In this way, RPA increases the degree of management accounting automation and provides a solution for overcoming the inefficiencies caused by manual work and process interruptions.

Besides the impact on financial and non-financial metrics, two case companies (companies C and D) making advanced use of RPA, have introduced new key performance indicators as a way of steering the implementation of RPA within their management accounting departments. Thus, they monitor the number of productive robots as a share of the total number of employees as well as the share of automated processes out of the total number of processes. Moreover, consultant B added that key performance indicators to steer and incentivise management accountants need to change. Most companies apply data quality, accuracy, or satisfaction of receivers with data provision as metrics. As RPA overtakes data processing and increases data quality, the performance indicators are no longer suitable either and need to be changed to include such things as quality and the satisfactory nature of consulting services of management accountants. However, none of the case companies examined have changed their management accounting metrics to date.

The respondents reveal that the degree of standardisation within management accounting increases in line with the implementation of RPA. Even though standardisation is not a direct outcome of RPA, it is both a precondition and an enabler of the efficient use of RPA. In this way, RPA provides a solution for the problem of missing standards and inharmonious process and system landscapes in management accounting, as introduced in Section 3.4.1. The case studies examined demonstrate that the degree of standardisation of input data and data sheets, as well as that of data collection and data processing, is increased. At the same time, the content and structures of existing standard reports are questioned and streamlined. Moreover, it is shown that RPA affects directly output quality and reduces the number of errors. This improvement can be explained by the rule-based nature of RPA, which excludes errors. Thus, the accuracy of figures improves and the overall quality and reliability of reports increases. As RPA stops working when process steps are ambiguous or errors occur, faults can be detected right at the time of occurrence and not just at the end of the entire process. In doing so, company B reports that RPA helps to reduce workload during month-end and prevents delayed reporting:

> *We use RPA to prepare, collect and consolidate month-end closing information from multiple business units. This used to be a highly manual, error-prone and time-consuming process. With RPA, we are able to perform data handling faster and recognise mistakes right when they occur. RPA really increases quality and accuracy and avoids delays due to late mistakes and lacking confidence.*

All case companies emphasise an increase in speed of execution as a direct impact of RPA. RPA works faster than human employees can and is available during non-working times, at night or at weekends. The reduced processing times available enable more rapid results and additional or more frequent analyses and they also release personnel capacities. In addition, delays from missing or late delivery of figures can be avoided. For example, chemicals company A uses RPA to perform month-end closing activities and thus was able to reduce its month-end closing time from five days to two days.

Moreover, the use of RPA in management accounting decouples work capacities from personnel resources. On the one hand, personnel resources are released by the automation of existing manual and repetitive processes with RPA. On the other, licenses for RPA are significantly less expensive than human personnel, a factor which enables access to additional capacities. As a result, the depth and level of detail of analyses, as well as the availability of additional data and reports, increases.

3.4.3 Organisation of Management Accounting and the Role of Management Accountants

3.4.3.1 Impact of RPA on the Organisation of Management Accounting

Regarding the organisation of management accounting departments, the analysis reveals that the introduction of RPA has had, so far, no impact at all on the organisational structure of management accounting. The case companies show that management accounting does not provide high-volume main processes for end-to-end automation with RPA. Instead, it is used in the form of a flexible automation solution for sub-processes and medium-to low-volume tasks across various main processes (cf. Section 3.4.1). Since no high-volume processes can be automatised within subdivisions, RPA does not offer any potential for the reorganisation of management accounting staff.

Surprisingly, the overall size of management accounting departments is not reduced by RPA. This is interesting, since RPA literature regards personnel savings as one of the most important and direct results of RPA (e.g. Lacity and Willcocks, 2016, Wanner et al., 2019). However, all of the management accounting departments examined report only fragmented savings of working hours across multiple employees. In addition, it might be possible, in the main, to achieve greater savings during month-end, which is one of the key bottle necks in management accounting. Most companies use the personnel released to carry out additional or more detailed analyses and to moderate personnel shortages in other areas. Thus, RPA constitutes a scalable automation solution that can be used to increase management accounting capacities regardless of personnel availability.

RPA initiatives are organised within a centre of excellence at all five case companies. This is in line with existing research on the organisation of RPA and is regarded as most suitable form of organisation (e.g. Hallikainen et al., 2018, Plattfaut, 2019). All RPA centres of excellence are affiliated to information technology or business excellence departments. Even though RPA can clearly be distinguished from information technology due to its low code nature, its organisational assignment to an information technology department is reasonable, because it is seen as an enabler of RPA and provides the necessary infrastructure. The centres of excellence examined steer all RPA initiatives within management accounting departments, contribute technological know-how and assume technical responsibility from RPA development to exception handling and operational adaption.

All companies report that process responsibility and operational competencies remain within the management accounting department, mainly because the RPA processes involve somewhat small volumes. Therefore, establishing RPA know-how within management accounting is detected nothing more than a minor organisational change. Two models are used that affect either the organisational structure by introducing a new organisational RPA unit or the roles of existing employees by tacking RPA responsibilities onto them. Companies A and D apply the former model and install an RPA single point of contact within their management accounting departments. Both have a dedicated RPA resource, which is used to interface with the centre of excellence. This single point of contact bundles and steers all RPA initiatives within management accounting and supports the identification of new processes as well as their operation and maintenance. Since company D has been operating a dedicated organisational unit ‘controlling systems’ within their management accounting division, which is responsible for all of the IT systems in use, they integrate their RPA single point of contact into this particular unit. In contrast, companies B, C and E, which are, in contrast, still at a rather early stage of RPA rollout within management accounting, apply the latter model and expand the roles of existing management accountants with RPA responsibilities. The process owners of specific RPA processes within management accounting obtain instruction in basic RPA knowledge and then manage the detection, operation and further development of RPA within their particular areas of responsibility. In summary, a digital automation string has been added to all of the management accounting departments examined at the time RPA was introduced, whereby the interface to information technology departments grows in importance. As the RPA technology becomes more and more intuitive and easier to operate, most companies plan that, in particular, basic processes, with few exceptions and a limited number of interfaces, will be developed by management accountants in the future.

Four out of five companies, of which all operate decentralised management accounting units, report that RPA reinforces the centralisation of management accounting. The decentralised units are responsible for either country divisions or business units and are operated under the responsibility of a central management accounting department. However, the decentralised units are subject to inefficiencies due to heterogeneous process and system landscapes and also due to a low level of utilisation of management accountants. The companies reveal that the implementation of RPA increases the centralisation of data processing. RPA is operated centrally for reasons of efficiency, compliance and utilisation and performs tasks for decentralised units. In this way, RPA increases the knowledge about and access to decentralised data for central departments without the need to involve decentralised employees. Moreover, the results show that RPA supports greater decentralised standardisation of management accounting processes, which is a precondition for the operation of RPA. This results in greater decentralised efficiency, since data handling tasks can be reduced and higher company-wide data quality and standards can be implemented.

3.4.3.2 Changing Roles of Management Accountants

In recent years, research on management accounting has emphasised the changing roles of management accountants, which is mainly driven by the introduction of information technologies, such as ERPS. The role of management accountants evolved from routine ‘bean counting’ into a so-called 'business partner' role, with a greater focus on management and the provision of value-adding support for decision-making and control (e.g. Goretzki et al., 2013, Järvenpää, 2007). The ERPS-induced role change described is also confirmed by the case studies conducted. In addition, the findings in this area reveal that RPA enhances the changes made to specific profiles. The overall routinisation of management accounting tasks further increases as RPA automates manual processes, which exist despite the use of ERPS. Thus, repetitive, manual work, such as report generation, data collection, data consolidation and preparation or analysis tasks can be automated. The head of RPA centre of excellence from company D explains as follows:

> *Despite many automation initiatives, our management accounting team still faced high workloads from boring and repetitive data crunching tasks. After we implemented RPA, the focus of activities changed to challenging numbers, developing measures, and consulting the business on the numbers. RPA took over the repetitive and non-value adding work.*

With the implementation of RPA, management accountants become the customer for reporting data, which is prepared by RPA. As a result, accountants change from performing an internal data and report generation role to performing a more analyst and consulting role. The focus is on managing exceptions, data interpretation, developing expedient measures as well as recommendations for action. From a data perspective, RPA enables management accountants to put more emphasis on forward-looking strategic information, as RPA carries out the preparation of actual and backward-looking data.

All respondents emphasise the increasing demand for RPA knowledge on the part of process owners within management accounting. Therefore, RPA further strengthens the trend towards more IT knowledge and IT affinity; this is a subject that has been discussed in existing research ever since ERPS were first introduced. Knowledge about the existing system landscape is an essential precondition, since RPA accesses systems in the same way a human would. Moreover, management accountants need a basic understanding concerning the functionality of RPA as well as its usefulness in identifying new candidates for processing. Company D calls their management accountants 'user story writers' and defines the identification, definition, and recording of RPA processes as basic RPA skills:

> *RPA will further change the job description and scope of work of management accountants. In our experience, it is more e cient and faster for accountants to identify,*

> *model and develop their own RPA processes. Therefore, the demand for IT knowledge in general and in relation to RPA in particular, is increasing. However, as RPA operates within a low code environment, it is intuitive and does not require deep programming skills, a factor that lowers the barrier to entry for non-a ne employees.*

In addition, RPA increases the need for process management skills among management accountants. All cases reveal process inefficiencies, which are driven mainly by the ad-hoc nature of reports and data analyses, as well as by high workloads and lack of capacity, with workloads peaking at the end of the month. Automation with RPA requires the optimisation and streamlining of processes, reports and data inputs prior to implementation. Therefore, RPA extends the role of management accountants by process re-engineering capabilities. As process candidates are often spread over multiple departments, RPA also expands the process responsibility of management accountants, transforming it into an end-to-end responsibility for entire processes. For example, the automaton of data collection and preparation for reporting with RPA not only requires the automation of data preparation within management accounting, but also the automation of data collection in operational departments.

3.4.4 Organisational Behaviour and Management Control

Even though RPA seems to have no direct impact on management accounting techniques and only minor impact on the applied financial metrics of measurement systems, respondents relate RPA to somewhat faster management decisions, increased decision quality and greater overall trust in accounts figures. This holds true for companies A and D, which use RPA at scale for data preparation and reporting tasks. In contrast, companies B, C and E, which are still at an early stage of RPA rollout, report no impact on management decisions.

The automation of data collection and the preparation of reports and month-end closing activities using RPA increases the availability of standard reports and monthly business figures. In particular, the time required for month-end closing activities could be reduced significantly from five days to two days by company A. Hence, RPA enabled faster management actions and increases flexibility. Moreover, the respondents emphasise the positive impact that RPA has had on the decision quality of managers. The rule-based nature of RPA excludes mistakes and so directly increases the overall accuracy and quality of data. In addition, the automation of repetitive, manual work enables a higher granularity of data and also enables management accountants to focus on detailed analyses and data interpretation work. The head of group controlling of company B explained:

> *With RPA we are able to avoid mistakes, which occur naturally during month-end with high time pressure. The improved number basis enables our management to take better actions and decisions. Moreover, as RPA relieves accountants from high workloads during month-end, they can develop more suitable measures for management action.*

Company A associates the improved data quality achieved by using RPA with greater trust in reports and reporting figures by management, which in turn has a positive impact on decision quality and decision speed. In the beginning, management was somewhat sceptical about the figures generated by RPA. However, during implementation, trust increased as RPA proved to be error-free in operation. This finding is an initial sign of the indirect effect of RPA on managers' trust.

Moreover, the use of RPA leads to improved cost control at both, centralised and decentralised corporate levels, at four out of five companies (companies A to D). As described in Section 3.4.2, RPA increases the availability of figures, the granularity of reports and the relevant capacities in management accounting. In turn, this increases the visibility of costs and enables tighter costs control. For example, company A uses RPA to update a particular key performance indicator dashboard for its top management on a daily basis, whereby before, it was only updated once a week due to a lack of capacity. By using RPA, it proved possible to increase the frequency of reporting as well as the availability of figures, which allowed faster management action and cost control. It is interesting to note that, in particular, RPA increased its decentralised costs control activities, which is confirmed by three case companies (companies A, B and D). For example, company A created a daily repair and maintenance spend report so as to ensure a rapid response to increasing costs and upcoming quality issues in relation to all products. Moreover, company D set up a new and fully automated cost reporting system for decentralised IT costs, such as licenses, which was enabled by additional capacity brought about by RPA. In this way, the company increased general transparency and also managed to reduce IT costs significantly.

Another interesting finding of the use of RPA in management accounting is reduced inter- and intra-departmental coordination work and less work having to be performed in other departments. Many regular management accounting processes involve multiple functions and demand input or actions from non-management accounting departments. This also holds true for coordination between centralised and decentralised management accounting units. The respondents report that RPA enables them to optimise and automate even small processes on an end-to-end basis. As a result, coordination and data handling efforts can be avoided, since RPA accesses decentralised data sources directly. Moreover, increased decentralised standardisation of processes and reports reduces decentral workload even further. For example, accountants from company E had to request marketing cost data on a monthly basis from their decentralised local marketing departments. Marketing prepared the figures, based on their own system and spreadsheet solutions in a report, and sent them to management accounting, where the numbers were validated, uploaded into the leading ERPS and processed further for monthly reporting. After automation, RPA accessed marketing systems directly, collected decentralised information, validated data based on predefined rules and inserted the figures into monthly reporting as well as into ERPS. In this way, it was possible to avoid time-consuming data handling and communication in both departments.

3.5 Discussion

The findings of the five case studies show that the adaption of RPA is consistent across organisations, even though they are at different stages of implementation. All companies started RPA initiatives outside management accounting and automated RPA tasks at a later point in time. For this reason, management accounting seems to be of subordinate importance for RPA, as it lacks volume and therefore has only limited economic impact. In general, RPA is identified as well-suited to the automation of management accounting tasks, such as budgeting, month-end closing and reporting. However, it turns out that the overall effect of RPA on management accounting is only minor. All of the management accounting departments examined reveal many rule-based, repetitive, manual data collection and data-handling tasks. Thus, in theory they fulfil the requirements for the use of RPA, as identified by prior research (e.g. Lacity and Willcocks, 2016, Wanner et al., 2019). Moreover, the results also reveal the absence of standardised processes and fragmented system landscapes, as well as informal management accounting routines. This confirms the heterogeneity of accounting system landscapes as shown by research (e.g. Granlund, 2011, Rom and Rohde, 2007). As a result, many interfaces requiring a high level of effort for data entry work and data transaction exist, which provides a further indication for the suitability of RPA to management accounting. An interesting point, though, is that management accounting contains a high number of low- to medium-volume tasks as part of its main processes and no high-volume use cases that can be automated with RPA in an end-to-end fashion. These tasks do not justify the use of heavyweight IT, which drives manual activity in management accounting. By using RPA as a lightweight solution, these low-volume processes could be automated. However, only a limited number of two to seven tasks and sub-processes have been automated at each company to date. Even though multiple RPA tasks are identified, deployment varies significantly between companies and thus only provides indications for changes of management accounting tasks.

No direct impact of RPA could be observed on management accounting techniques or on methods and controls. This finding is not surprising, since the introduction of ERPS did not affect techniques significantly in the beginning. As shown, only one company used RPA to change its planning technique from a three-year budget to a rolling forecast. RPA enabled this change by performing all data-handling activities and thus increasing available capacity. However, the example is not reproducible across the board and does not confirm any direct impact of RPA on techniques. Overall, RPA is used to automate the execution of existing techniques without affecting the logic involved. The only factor that did change, though, are the results as outcomes of the management accounting techniques. The cases examined clarify that RPA increases the efficiency and effectiveness of management accounting for the tasks being automated. On the one hand, the implementation of RPA brings about a marked improvement in speed of execution as well as quality of output. On the other, RPA has the indirect effect of reinforcing standardisation as a precondition for automation. Moreover, RPA decouples processing capacities from personnel numbers. This enables more detailed analyses and greater availability of additional data and reports. Regarding financial metrics, all respondents confirm that RPA has no impact on additional financial key performance indicators. However, what can be observed is improved access to and expansion of non-financial key performance indicators. Research indicated that ERPS expanded the availability of non-financial measures by integrating transactional and financial information (Sánchez-Rodríguez and Spraakman, 2012). RPA reinforces this development by automatically connecting additional non-integrated sources to ERPS and financial reports.

The analysis reveals that RPA has no impact on the organisational structure of management accounting. This is interesting, as research relates RPA to a reduction in personnel numbers, which can bring about reorganisation, given that demand for personnel decreases and tasks change or are redistributed (e.g. Lacity and Willcocks, 2016, Plattfaut, 2019, Wanner et al., 2019). However, none of the case companies examined were actually able to implement personnel reductions. This absence of impact on accounting personnel can be explained by the early stage of implementation as well as by the lack of high-volume RPA process candidates, factors militating against any reduction in a full complement of personnel. What RPA does bring about is the introduction of a new RPA department within management accounting or the expansion of existing roles of accountants through the addition of RPA-related responsibilities. This finding can be regarded as minor change in the organisation of accounting activities at all of the case companies. The only notable change that could be observed is the increased centralisation of data processing and increased decentral routinisation. RPA increases the formalisation of routines by replacing informal routines in decentralised units for, for example, data preparation or report generation, together with an increased standardisation and automation of tasks. The changes to the activities of management accountants caused by RPA were identified to be largely as expected. With RPA, management accountants become the customers for reporting data, which is prepared by RPA. Therefore, they change from performing an internal data and report generation role to performing a more analyst and consulting role. In order to be able to operate RPA, the role of management accountants also requires deeper IT and RPA knowledge. However, the change in role only affects a limited number of accountants who are responsible for the few tasks automated with RPA. As the work quota of almost every accountant contains manual tasks, it is expected that RPA has the potential to change the roles of management accountants at a scale when rolled out further.

With regard to management control, the example of two case companies shows that RPA directly increases and accelerates the availability of standard reports and monthly reporting data, as reporting activities are automated and accountants have more time for month-end closing tasks. Therefore, RPA enables somewhat faster management decisions, increases overall decision quality and has an impact on the routines of report customers. This improved decision quality is brought about by the rule-based nature of RPA, which prevents errors, thereby directly increasing the overall accuracy and quality of data. Respondents from company C also reveal that managers' trust in accounting information increases in line with the improved data quality. This finding amounts to an initial indication of the indirect impact of RPA on management trust and needs to be examined further. In addition, it is evident that the deployment of RPA leads to less time spent on inter- and intra-departmental coordination efforts as well as a reduced effort in other departments.

Although management accounting tasks theoretically meet the requirements for the use of RPA, only a small number of two to seven tasks has been automated to date by the companies examined. The interview findings provide several explanations for this. First, RPA is a young technology and at a comparably early stage of implementation. The companies examined started implementation at the earliest three years ago and focused their initial activities on high-volume processes with high economic benefits. These are found only rarely in management accounting. The low volume and resulting lack of priority can therefore explain the low degree of RPA implementation in management accounting. Once task suitability is established, the impact of RPA on management accounting is expected to unfold in the long term. Second, the implementation of RPA is still complex and not as intuitive as stated by software providers. As a result, implementation cannot be carried out by accountants themselves and requires the assistance of RPA and IT experts. This increases implementation costs and slows down the speed of automation. Moreover, IT departments, as existing institutions, seem to be reluctant to change using RPA, as the technology intervenes in IT systems without being under the control of the IT department. Third, managers have also been identified as slowing down the implementation of RPA. This is because changes to management accounting practices may affect financial data and reports, which are critical to management control and should remain constant.

The respondents emphasise that the introduction of RPA is based on intentional, rational decisions and is driven by economic reasons and the need for faster access to data, as the business environment becomes increasingly vulnerable. The companies aim to save personnel costs, overcome inadequate personnel capacity, increase flexibility and improve the availability of data. For that, RPA constitutes a suitable automation solution, which makes it an important driver of change in management accounting. Institutional theory offers an appropriate explanation for potential changes. In this context, management accounting systems can be regarded as rules defined in manuals of procedure, whereas routines are the practical application. The findings made reveal that RPA as a new technology changes existing rules for the automation of those tasks. Moreover, it becomes apparent that many routines were never explicitly set out in the form of rules and instead follow somewhat informal procedures; examples of this is the way how data is prepared outside leading ERPS or deviating reports in different business units. For this reason, the main impact of RPA was identified as being in the change to management accounting routines brought about by the automated performance of tasks, whereby routinisation increases through process standardisation and outcomes are improved. As a result, tasks become less transactional, with less manual data handling and manipulation work and develop more into analysis and interpretation activities. However, up to now, the impact on routinisation is rather limited. This is because change in management accounting practices can be characterised as evolutionary, while the rollout of RPA is still at an early stage in all five case companies.

The degree of impact of RPA on the change of management accounting can also be explained with the type and size of companies that apply RPA. Companies that can exert more power over their suppliers or customers are more likely to have a high degree of integration of their ERPS and limited dependence on external systems. The applicability of RPA decreases as main processes are integrated and little system interruptions exist. In contrast, companies with a stronger dependence on customer or supplier systems often lack integration, face more system interfaces and manual effort. Therefore, the overall applicability is higher as more RPA task candidates exist. The same holds for companies with different sizes measured as total revenue. Smaller companies operate rather heterogeneous IT systems with more informal processes and rules. This makes them better suited to RPA compared to the management accounting of larger companies with more professional accounting systems and a higher degree of integration.

3.6 Conclusion, Limitations and Future Research

Information technologies play an ever-greater role for companies and their management accounting disciplines. Despite the introduction of ERPS in the 1990s and other technologies, such as business intelligence systems, management accounting still lacks integration and comprises many manual tasks. The aim of this research is to examine the impact of RPA as new automation technology on management accounting tasks and techniques as well as on the organisation and role of management accounting. To address the research question, a cross-sectional multiple case study with five case companies from different industries and stages of implementation that apply RPA in their management accounting departments was used. In summary, RPA is identified as a suitable solution capable of further improving the degree of automation in management accounting. However, as management accounting lacks high-volume processes for automation with RPA, its overall impact is minor and not comparable to the introduction of ERPS in management accounting or, indeed, to the application of RPA in accounting and auditing functions.

The companies examined show that only a small number of management accounting tasks have been automated to date. RPA is used to automate the performance of tasks, whereby routinisation increases by means of process standardisation. As a result, the findings suggest that management accounting tasks become less transactional with less manual data handling and manipulation effort and develop more into analysis and interpretation tasks. Moreover, it is evident that RPA does not drive the adoption of new accounting and control techniques. Nor are existing key performance indicators affected, although in some cases improved access to and expansion of non-financial key performance indicators were observed. Overall, the cases clarify that RPA increases the efficiency and effectiveness of management accounting. Thus, RPA directly improves the speed of execution and the quality of outputs and indirectly drives standardisation. The only notable change to the organisation of management accounting is the establishment of RPA responsibility within management accounting, increased centralisation of data processing and increased decentralised routinisation via the adaption of RPA. Besides these elements, no impact on the organisation and size of management accounting could be observed. With respect to the role of management accountants, it was shown that accountants become customers for reporting data prepared by RPA. Therefore, their role changes from that of internal data and report generation into a more analyst and consulting role and requiring knowledge of RPA. This finding confirms existing research on the impact of technologies on the role of accountants as well as on the impact of RPA on the role of finance employees. It also extends the changing roles brought about by RPA to management accounting. With regard to management control, the cases examined reveal that RPA enables somewhat improved costs control and more rapid management responses.

In general, RPA must be viewed as one more tool in the automation toolbox supplementing existing IT applications and closing present gaps in automation, as the system landscape of most companies is still heterogeneous with many interfaces and manual workarounds. Besides the lack of high-volume tasks, another explanation for the minor impact of RPA can be found in the early stage of implementation of RPA in management accounting. As this technology is developing rapidly, its impact may increase in the future. A major precondition for use at scale was identified in the improved operability of RPA tools. As management accounting tasks are low volume by nature, accountants need to be able to automate them without external support, in order to be able to achieve economically viable implementation and operation costs. The interviewees predict that RPA will develop into a flexible automation solution for all management accountants just as spreadsheet solutions with easily programmable actions did some decades ago.

This paper makes several noteworthy contributions. First, it lays the foundation for research on RPA and management accounting, as to date no research in this field exists. It shows that management accounting and the activities of management accountants are changed slightly by the implementation of RPA. As many routines are not explicitly set out in rules and follow somewhat informal procedures, RPA changes the routines of management accountants by carrying them out automatically as well as by bringing about greater task standardisation and routinisation. Second, a generally suitable task classification is introduced that guides the selection of tasks for automation with RPA in management accounting. Management accounting provides six fields of application for RPA, namely transfer of data, processing of data, analysis of data, preparation of data, operation of systems, and transmission of data as well as communication. Third, an analytical framework for RPA and management accounting change based on existing research on the impact of technologies on management accounting as well as based on research on the selection of RPA processes is introduced. This framework can be used for future research on RPA and management accounting. From a user perspective, the tasks identified may encourage corporate executives to leverage RPA in their management accounting departments or guide them to further expand their existing RPA initiatives to the demonstrated fields of use. Moreover, the benefits introduced may serve as a guideline for reviewing the benefits already experienced due to RPA. Furthermore, the described role change can help to adapt the training and hiring criteria used by management accountants.

A number of limitations need to be considered. First, the use of RPA is still in its infancy and only few companies use RPA in management accounting. Hence, statements about its applicability, potential benefits and costs can only be generalised to a limited extent. Second, RPA technology is changing rapidly. Thus, reported results may change as firms gain experience with RPA. Third, the selection of RPA case companies is not exhaustive and no company that rolled out RPA extensively over all possible use cases was included. Since I did not identify such a company after extensive research, I assume that it can be explained by the early stage of RPA. Nevertheless, I included companies from multiple stages of implementation, with different sizes and from various industries, in order to obtain a holistic overview. Fourth, experts may have overstated the potential of RPA or else confused its impact on management accounting with that of other technologies. To overcome this, process documentations, cost calculations and other reports were included, in order to confirm automation potential and the resulting benefits. Fifth, there is a possibility that the analytical framework used may have skewed the results. However, it was only used to structure the analysis undertaken and both dimensions were used before in previous research on RPA or ERPS. Sixth, data collection was carried out during a limited period of two month, even though some authors recommend conducting long-term studies to assess change. To overcome this, the entire implementation journey was discussed, in order to tease out chains of causation.

This research aims to lay the foundation for future conversations and research in the field of RPA and management accounting. In general, additional research, based among other things on longitudinal methodologies, would be of interest as a way of linking RPA and management accounting change and continuity. Conclusions on the impact on change and chains of causation can be drawn only after a few years. Moreover, the question whether the minor impact of RPA on management accounting is a general observation or only caused by the early stage of adaptation should be examined further. As research indicates that RPA becomes more and more intelligent by being combined with, for example, machine learning technologies, researching the applicability of intelligent automation on management accounting as well as potential resulting impacts would be of interest. In this context, process identification and automation based on intelligent technologies, such as process or task mining, are another interesting subject of investigation. The nature of management accounting, which features rather small tasks in multiple systems, indicates a high level of suitability for these technologies. The findings also reveal that the roles of management accountants are changing as are the skills required. Management accountants need to expand their skills relating to, for example, process management, RPA development or operation. The respondents also point out that there is a high degree of uncertainty about the role of human employees working alongside RPA. Future research should identify the roles that are most susceptible to automation with RPA. Moreover, the impact of RPA on the work of management accountants, the skills and competencies required to work alongside their digital colleagues, and the roles that management accountants are playing in the digital transformation should be examined. As the findings suggest that trust increases in line with intensified use of RPA, research on the role of RPA on management trust in automatically generated data may be another interesting field of research.

4 Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation

Abstract

Advances in artificial intelligence (AI) are changing the nature of work and enable an increasing automation of tasks. The trend around AI technologies has also reached robotic process automation (RPA). To date, RPA is known as a software solution that performs simple and routine tasks based on clearly defined rules. However, past research indicates that through the application of AI and machine learning technologies, RPA is starting to get 'smart' by including intelligent features. Since little is known about the capabilities of intelligent RPA in academia, this paper examines how AI impacts the capabilities and applicability of RPA. Based on case studies with global RPA software providers and RPA integrators, evidence for cognitive capabilities within RPA is examined within the boundaries of a definition of cognitive intelligence. The paper also discusses the general necessity for cognitive intelligence within RPA software.

Author: Johannes Viehhauser

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4.1 Introduction

Artificial intelligence (AI) is dramatically changing the nature of work. Even complex tasks, which were previously performed exclusively by human knowledge workers, are increasingly being automated by machines (Dias et al., 2019, Koorn et al., 2018). The increasing automation is made possible by recent advances in artificial intelligence and machine learning (ML) technologies, the increasing processing power and speed of computers, and the availability of vast amounts of data (French, 2012, Gupta et al., 2018). A recent study by the Massachusetts Institute of Technology spanning 2,200 global business leaders and managers in 2020 reveals that nearly two thirds of the respondents expect artificial intelligence to significantly change corporate organisations. The study also reveals that the majority of companies have already initiated projects with artificial intelligence and are progressing in the implementation of artificial intelligence in their operating environments (Columbus, 2020). This makes it clear that artificial intelligence is not a tech buzzword anymore but has arrived in the corporate world (Huang and Rust, 2018).

The trend around artificial intelligence technologies has also reached robotic process automation (RPA), which is a comparably new and emerging technology that has gained significant importance in the corporate world and academia in recent years. Per definition, RPA is an umbrella term for computer programs that mimic and replicate human activities by imitating manual, screen-based manipulations (Lacity and Willcocks, 2016, Penttinen et al., 2018, van der Aalst et al., 2018). Various researchers indicate that sophisticated RPA solutions are starting to get 'smart' and include artificial intelligence and machine learning capabilities to recognise and process unstructured data, and to learn in cooperation with human users (e.g. Hofmann et al., 2019, Plattfaut, 2019, Wanner et al., 2019).

However, research in the field of RPA mainly focuses on simple RPA, which is limited to the execution of well-structured routine tasks based on explicit and predefined rules and substitutes the 'arms' and 'legs' of human workers. This typically includes tasks at the interface between systems, such as extracting, manipulating, processing, or transmitting data (Plattfaut, 2019, Wanner et al., 2019). Little is known about RPA with capabilities based on artificial intelligence, even though it appears to be a major trend in industry. Agostinelli et al. (2019) focus on intelligent RPA by analysing different RPA software and identify limited self-learning abilities within the examined RPA solutions (Agostinelli et al., 2019). Other authors address intelligent

RPA only marginally as an idea or early indication but do not provide in-depth analyses (e.g. Plattfaut, 2019, Syed et al., 2020, van der Aalst et al., 2018).

Two distinct approaches exist in the discussion about RPA and intelligence. On the one hand, authors indicate that the RPA software itself can become more intelligent by integrating cognitive capabilities, self-learning mechanisms, natural language processing (NLP), or computer vision. As a result, intelligent RPA would be able to support more complex and less structured tasks without the need for external software (Plattfaut, 2019, van der Aalst et al., 2018, Wanner et al., 2019). The opposing stream defines RPA as software that strictly relies on predefined rules and is not intelligent itself, since intelligence contradicts the actual definition as rule-based execution engine. The required intelligence is provided through external technologies and integrated into platforms. Therefore, new terminologies such as intelligent process automation or intelligent automation are introduced (Hofmann et al., 2019, Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019). However, besides some first attempts to define RPA with artificial intelligence, there is a lack of profound research on the subject. Most authors only indicate the development towards RPA and artificial intelligence as future opportunity, introduce definitions, or point out early machine learning or artificial intelligence capabilities of RPA without examining them in detail (Hofmann et al., 2019, Syed et al., 2020).

Given the increasing importance of and attention on RPA and artificial intelligence in industry as well as the lack of research in academia, this paper raises the questions of how intelligent RPA is and whether or not RPA needs intelligence at all and thus asks: *How and to what extent is artificial intelligence integrated into RPA and which e ects from artificial intelligence result on the capabilities of RPA as well as on its applicability, with focus on suitable task characteristics?* Due to the limited theoretical understanding and present dynamics in the field of intelligent RPA, a multiple case study approach is applied (Eisenhardt and Graebner, 2007). Specifically, rich field and archival data from nine global RPA software providers and six RPA integrators are used. Moreover, an operationalised definition of cognitive intelligence as a subdomain of artificial intelligence serves as framework to assess the level of intelligence of RPA solutions.

The results of the conducted case studies show that RPA has only very limited cognitive capabilities and, by its very nature, remains a rule-based execution engine. Only intelligence that enables RPA to work more efficiently and expand its applicability without affecting the predictability and accuracy of outcomes is built into RPA engines. However, the applicability of RPA for tasks requiring intelligent capabilities is increased by combining RPA with external solutions. All of the examined RPA providers offer platforms to modularly add intelligent capabilities to RPA, which indicates that the evolution towards more intelligent capabilities takes place based on external capabilities rather than within the RPA engine itself. Finally, the impact on process and task suitability is examined. The findings reveal that increasing intelligence expands the potential fields of application of RPA, since the necessity for structured data input, standardisation, and process stability becomes less important.

This research comes with several contributions to the growing literature on RPA. It provides the first holistic analysis of RPA and intelligent capabilities and introduces a framework to assess the level of intelligence, which can be applied and further developed for future research. Moreover, it introduces the approach of modular RPA platforms to the newly emerging terminology intelligent automation and therewith further details and operationalises intelligent automation. Third, it disproves the hypothesis of RPA becoming and requiring extensive intelligence and guides research to further investigate RPA platforms rather than RPA engines (Hofmann et al., 2019, van der Aalst et al., 2018). The paper also yields important practical implications, particularly for RPA software providers. It suggests detailed cognitive capabilities that are beneficial for RPA and should be incorporated to further improve the overall capabilities of RPA solutions.

The research paper is organised as follows: In Section 4.2, fundamental knowledge on simple RPA is introduced and artificial and cognitive intelligence are defined. In Section 4.3, the applied research method, data sources, and the analysis approach are described. Based on a framework for cognitive intelligence, the classification and analysis of RPA as well as RPA platforms and their level of cognitive intelligence is discussed in Section 4.4. The section also presents implications for process and task suitability. Finally, key findings are summarised in Section 4.5 and limitations as well as future research opportunities are discussed in Section 4.6.

4.2 Background

4.2.1 Definition and Introduction to Simple RPA

To date, academic research has put focus mainly on simple RPA (Hofmann et al., 2019, Lacity and Willcocks, 2016). Even though there is no commonly agreed upon definition for RPA in academia, a widespread used commercial definition has been established by Tornbohm: “RPA tools perform [if, then, else] statements on structured data, typically using a combination of user interface interactions, or by connecting to application programming interfaces (APIs) to drive client servers, mainframes or HTML code. An RPA tool operates by mapping a process in the RPA tool language for the software robot to follow, with run time allocated to execute the script by a control dashboard" (Tornbohm and Dunie, 2017).

RPA is part of the business process management domain and aims to automate existing processes based on available IT infrastructure by applying robots to digitally perform tasks (Lacity and Willcocks, 2016, van der Aalst et al., 2018). RPA is based on a computer program or single software instance with scripted language that mimics and replicates human activities by imitating manual, screen-based manipulations and reacting to events on the screen (e.g. Lacity and Willcocks, 2016, Penttinen et al., 2018, van der Aalst et al., 2018). The software can be configured by humans to capture and interpret data from existing applications, manipulate data, or communicate with other digital systems. RPA robots can either be traditionally programmed, configured by using a graphical user interface, or trained based on recorded process steps (Wanner et al., 2019). A special feature that distinguishes RPA from traditional back-end automation solutions is that it operates on graphical user interfaces or computer systems in the way a human would. It can, therefore, be adapted and interact with a wide range of application interfaces and software systems without changes to applications. Besides, RPA is also able to use APIs to interact with standard software (Hofmann et al., 2019, Plattfaut, 2019, Wanner et al., 2019). The definition of RPA is mainly valid for simple RPA solutions. That means, RPA without any form of cognitive intelligence, which has been the primary focus of research on the domain so far.

A variety of authors in the research field of RPA has put focus on the examination of benefits from automating processes and tasks with RPA. The studies are mainly based on single or multiple case studies in various industries and geographical regions. They identified the technologies' ease of implementation and ease of use, increased operational performance, flexibility and availability, a high level of output quality, and adherence to compliance requirements as core advantages. First, RPA is based on a bottom-up rather than top-down approach, which means that the implementation is initiated and driven by non-programmers and advanced IT skills are not needed. As a result, RPA can be implemented in a short time frame and allows for a high degree of agility and flexibility (Hallikainen et al., 2018, Lacity and Willcocks, 2016, Plattfaut, 2019). Another advantage of RPA is that it is non-invasive and interoperable. The software is technology independent and can operate on various legacy systems and platforms. Also, no redesign of existing processes is needed, since RPA works based on existing processes and simply imitates human action (Penttinen et al., 2018, Plattfaut, 2019, van der Aalst et al., 2018). Second, research emphasis core advantages of RPA from an increase in operational performance. Robots outperform humans in terms of efficiency and execute rule-based tasks with reduced handling times. The shift from manual and repetitive work to RPA robots relieves employees from non-value adding tasks (Hofmann et al., 2019). This also results in a reduced need for employees and therewith reduced personnel costs (Hallikainen et al., 2018, Hofmann et al., 2019, Lacity and Willcocks, 2016). In addition, robots are able to work 24/7 and increase productivity, availability, and continuity of services (Syed et al., 2020). Third, RPA increases the quality of output by eliminating transactional errors such as incorrect data transfer or missed process steps. Due to its rule-based nature, RPA works with a high degree of accuracy and only performs tasks which are clearly correct (Penttinen et al., 2018, Syed et al., 2020). Last, RPA commands a high level of auditability as well as increased compliance. All tasks and actions performed by RPA are logged and traceable. This enables a high level of security, auditability, and compliance (Hallikainen et al., 2018, Lacity and Willcocks, 2016).

4.2.2 Process and Task Suitability for Simple RPA

The assessment of whether a process or task is suitable for automation with RPA or not is mainly based on the process itself, the involved systems, and the required data. Due to the rule-based nature of simple RPA, it appears to be most important that the process follows a defined structure, is standardised, and consists of clearly defined rules. Processes with a high degree of standardisation reduce the implementation effort, increase implementation speed, and raise the overall probability for project success (Asatiani and Penttinen, 2016, Geyer-Klingeberg et al., 2018, Lacity and Willcocks, 2016). To ensure an economic viable operation, a high volume in terms of frequency of repetitions and duration of execution is critical (Dias et al., 2019, Penttinen et al., 2018). Moreover, the processes as well as their environments need to be mature and stable, since processes with a low probability of exceptions and predictable outcomes reduce failure and maintenance costs (Penttinen et al., 2018, Wanner et al., 2019). Another process criterion is its proneness to human errors. According to Geyer-Klingeberg et al. (2018), processes with high failure rates are particularly suitable for RPA, since an automation reduces failure costs. In addition, processes with a high degree of manual work are good automation candidates for RPA and provide greater potential for automation (Geyer-Klingeberg et al., 2018). Finally, Dias et al.

(2019) argue that the nature of data input is critical as well. Processes can only be automated with RPA if all required data are available in digital format and with a sufficient quality and structure.

4.2.3 Artificial Intelligence in the Context of RPA

There is early evidence that RPA solutions start to include more advanced features based on artificial intelligence technologies, which enable the support of more complex and less defined tasks (e.g. Plattfaut, 2019, van der Aalst et al., 2018, Wanner et al., 2019).

In order to decide whether a system or software is intelligent, one first needs to define the term 'intelligence'. For computer scientists, 'intelligence' refers to artificial intelligence, machine intelligence, or computational intelligence as a subset of human cognitive behaviour (Feigenbaum, 2003). It is common in research to apply the concept of human intelligence to approach the definition of artificial intelligence as machines that exhibit aspects of human intelligence (Feigenbaum, 2003, Huang and Rust, 2018). Thereby, the human intelligence literature considers intelligence as "biopsychological potential to process information [...] to solve problems or create products that are of value in a culture" (Gardner, 2000). Intelligence is regarded as ability to learn from experience and adapt to the environment (Gardner, 1983). Research on artificial intelligence applies the concept of machine intelligence to mimic human intelligence in domains such as perceiving, communicating, learning, problem-solving, reasoning, or acting (Russell and Norvig, 2002). The origins of the discussions to define artificial intelligence go back to the work of Alan Turing (1950), who proposed an operational definition as part of a test for computational intelligence (French, 2012, Hernández-Orallo and Dowe, 2010). However, up to date, there is no commonly agreed-upon definition for artificial intelligence.

This research refers to the definition of artificial intelligence by Kaplan and Haenlein (2019), who define artificial intelligence as "the ability [of a system] to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption". This definition is particularly suitable in the context of RPA, since it builds on management literature and specifically targets application in business environments. The authors introduce three types of intelligence: cognitive intelligence, such as pattern recognition or systematic thinking, emotional intelligence, such as adaptability or self-awareness, and social intelligence, such as empathy or teamwork. Since most of the artificial intelligence systems used in the context of RPA aim to emulate cognitive intelligence by generating a cognitive representation of the environment as well as by learning from past experiences to inform future decisions, it is sufficient to focus on cognitive intelligence to assess the degree of 'intelligence' of RPA (Plattfaut, 2019, van der Aalst et al., 2018). Humanised artificial intelligence with emotional and social intelligence is not included in the analysis, since it is not available yet (Kaplan and Haenlein, 2019).

Moreover, intelligence can also be classified into weak and strong artificial intelligence. The hypothesis of weak artificial intelligence constitutes that machines act as if they were intelligent, apply artificial intelligence only to specific areas, and are not able to solve problems autonomously. In contrast, strong or general artificial intelligence assumes that machines actually think and do not just imitate human intelligence, apply artificial intelligence in various areas, and are able to solve problems autonomously (Kaplan and Haenlein, 2019, Russell and Norvig, 2002). In the context of intelligent RPA and this research, cognitive intelligence is considered as form of weak artificial intelligence (Huang and Rust, 2018).

4.2.4 Classification Framework for Cognitive Intelligence

To analyse cognitive capabilities of RPA, cognitive intelligence is operationalised by cognitive computing. The technology is inspired by the human mind and aims to interact with external sources, process and understand contextual meaning, learn from past experiences, and draw conclusions based on large volumes of data from various sources (Gupta et al., 2018, Modha et al., 2011). Cognitive computing includes technologies, such as natural language processing, machine learning, neural networks, or automated reasoning (Davenport and Kirby, 2016).

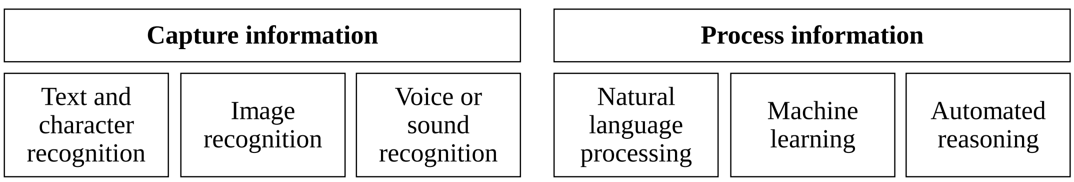

Figure 4.1: Classification framework for cognitive intelligence.

Cognitive systems comprise two core capabilities: information capturing and information processing (Davenport and Kirby, 2016, Gupta et al., 2018). For this research, they are applied as a framework to discuss and identify intelligent capabilities of current RPA software solutions in the context of implemented use cases (cf. Figure 4.1). The first dimension, capturing information, includes the collection of data and information as well as the perception and observation of the environment. Data collection includes information from text, vision, sound, or voice. The second dimension, processing information, includes capabilities to analyse and interpret contextual meaning via NLP, to learn via machine learning capabilities, and to reason and take decisions via automated reasoning. NLP uses computational techniques to understand natural language and produce human language content. It thereby serves as a basis for human-machine or machine-machine communication (Hirschberg and Manning, 2015). Machine learning solutions provide the ability to recognise patterns, to learn, to develop solutions, and to adapt to new circumstances based on the applied learning algorithm. In the context of this paper, machine learning refers to supervised learning methods that learn based on the mapping of a given set of input variables to a given set of predefined output variables. In contrast, the more sophisticated approach is unsupervised learning, where labeled outputs do not exist and the algorithm itself interprets the input variables and draws conclusions (Kaplan and Haenlein, 2019). Automated reasoning allows computers to autonomously reason about knowledge they have gained completely, or almost completely, answer questions, and draw conclusions (Rich and Feldman, 1992).

4.3 Methodology

4.3.1 Research Approach

Given the limited theoretical understanding and present dynamics in the field of intelligent RPA, this paper applies a multiple case study approach (Eisenhardt and Graebner, 2007, Yin, 1981). The multiple case study approach is broadly used in information systems (IS) research and is particularly suitable for research on newly emerging technologies in organisations such as RPA in combination with cognitive intelligence (Alavi and Carlson, 1992, Conboy et al., 2012, Orlikowski and Baroudi, 1991).

The setting of this research paper is the global RPA industry in the year 2020 and consists of RPA software providers and RPA integrators, who apply the software at implementation projects. The setting is appropriate to address the research question for several reasons. First, since the focus of this paper is put on the latest available RPA software and its applicability, it is necessary to target the developer and integrator ecosystem to fully cover latest available solutions. The former have an in-depth knowledge about their own RPA solutions and bring in a competitor outside-in view. They can contribute state-of-the-art developments of simple and intelligent RPA solutions and reflect current technology limitations. RPA integrators take an application-driven perspective and serve as interface between software providers and end users. They have an in-depth knowledge on market requirements and the practical applicability of both available simple and intelligent RPA solutions. End users in the form of industry companies are not included in the setting, since they have a rather ex-post view and potentially lack a holistic understanding of latest market developments. Their perspective is covered by RPA integrators. Second, it is important to put a global view on the market for RPA software providers, since the software providers have a global reach and are located mainly in Europe and North America. To address regional peculiarities in terms of market requirements and technological progress, RPA integrators from all major markets are included. Third, since the paper puts focus on state-of-the-art technologies, the concentration on a limited research period ranging from March to June 2020 is appropriate.

TABLE 4.1: Interview panel.

Company	**Origin**	**Interview and archival data**		
		Position of interviewee	**Interview duration (IV/FU)**	**Archival data**
RPA provider A	North America	Director Partnerships	75/15 min	6 PS, 1 PR, 2 CD
RPA provider B	North America	IT Solution Manager	80/15 min	4 PS, 2 PR, 1 CD
RPA provider C	Europe	IT Solution Manager	60/10 min	6 PS, 2 CD
RPA provider D	Europe	Business Development Manager	75/20 min	2 PS, 2 CD
RPA provider E	Europe	IT Solution Manager	60 min	2 PS, 2 CD
RPA provider F	Europe	Director RPA	55 min	4 PS
RPA provider G	North America	Director RPA and AI	70/15 min	1 PS, 1 PR, 5 CD
RPA provider H	Europe	Global Head Internet of Things	80/30 min	4 PS, 2 CD
RPA provider I	Europe	Account Manager	50/10 min	3 PS, 1 PR
RPA integrator A	Europe	Managing Director	50 min	2 PS
RPA integrator B	North America	Managing Director	50 min	1 PS, 1 CD
RPA integrator C	Europe	R&D Manager	55 min	1 PS, 1 CD
RPA integrator D	Middle East	Managing Director	55 min	1 PS
RPA integrator E	Europe	Innovation Manager	90 min	2 PS
RPA integrator F	Asia	Managing Director	45 min	1 PS

Legend: IV = Interview, FU = Follow-up interview, PS = Product specification, CD = Case documentation, PR = Press release

For the purpose of this research it is important to get a broad overview on available RPA solutions and their capabilities to optimally cover the market. Therefore, a broad sample of 15 companies is selected. The theoretical sampling is in line with Eisenhardt and Graebner (2007), since the approach is exploratory rather than testing of hypotheses. The applied sample consists of nine RPA software developers, including the three globally leading market players, and six

RPA integrators (cf. Table 4.1). Initially, the leading RPA software developers were identified based on existing research (e.g. Lacity and Willcocks, 2016, van der Aalst et al., 2018), which was also confirmed by the conducted interviews. The panel was then expanded with additional providers based on recommendations from industry experts during the first wave of interviews. For a bottom-up validation, six RPA integrators, who already worked with the examined RPA software tools and implemented the underlying case studies, were included. The panel is selected for several reasons. First, the leading RPA providers, as key market drivers, ensure that the latest and most widely used solutions are included in the research. Second, additional RPA providers supplement the panel, since some offer high technology niche products or have strong capabilities in cognitive intelligence. Third, the six integrators are important to bring in an application and market perspective. Since market requirements differ, integrators from Europe, North America, Asia, and Middle East are selected to cover markets with different requirements for automation.

4.3.2 Data Sources

As shown in Table 4.1, several data sources are used: (a) semi-structured interviews with top management as well as technology and innovation managers from RPA software providers and RPA integrators, (b) informal follow-up interviews and discussions, and (c) case documentations and archival materials.

The interview process consisted of three waves. In the first wave, three interviews with global leading RPA software providers were conducted with focus on their RPA history, product offering, and concrete use cases that they achieved with latest RPA solutions (Kokina and Blanchette, 2019, Wanner et al., 2019). In addition, the terminologies for RPA and cognitive intelligence were examined and the importance of the research question was validated and confirmed. In the course of the interviews, additional RPA software providers were identified and a second wave of six interviews with second and third tier RPA providers was conducted. In the third wave, six interviews with RPA integrators served as bottom-up validation for the solutions and use cases discussed during the first two waves of interviews.

The approach of semi-structured interviews, which is widely used in IS research and well suited for the research question, is applied for data collection. Therefore, an incomplete script was used and continuously further developed during the interview process. The script followed the recommendations by Myers and Newman (2007). The first part covered the informants background, current role, and experience with RPA as well as a detailed overview on the companies' history and development. The second part focused on the companies' RPA offering with regard to intelligent capabilities as well as key technology limitations. Thereby, the framework for cognitive intelligence was used to discuss and identify potential intelligent capabilities of RPA software in the context of implemented use cases (cf. Section 4.2.4). The goal was to understand the role of intelligence for RPA solutions, the capabilities that are incorporated into RPA, and the role of RPA platforms and interfaces for external technologies. The third part targeted process and task characteristics required for simple as well as for intelligent RPA (cf. Appendix A.5). The interviews lasted between 45 minutes and 90 minutes, were conducted via phone, and recorded.

Several measures were taken to ensure data validity. First, a broad panel of RPA software providers has been applied and the results were critically discussed with external sources such as RPA integrators. The technical capabilities, as stated by the software providers, were critically challenged and only accepted if concrete use cases prove the application of features. This helped to increase the overall understanding and data validity. Also, the transcripts of all interviews were sent out and reviewed by the informants to ensure accuracy. To overcome a potential elite bias, interviewees from various functional areas and hierarchical levels were included. From a technical perspective, interviewing techniques such as non-direct speech and open questions were used to receive accurate information. Finally, a detailed overview of the research project was given beforehand and anonymity was granted to overcome a potential lack of trust.

The paper also uses data from archival materials. As preparation for the interviews, available data on technologies and use cases were collected from the RPA providers' homepages, press releases, and public reports. During and after the interviews, the interview partners provided additional background material on the discussed contents and use cases.

4.3.3 Data Analysis

The data analysis began with a within-case analysis of the collected information from interviews with RPA software providers as well as of case studies and archival material. Thereby, the capabilities of RPA as well as of RPA platforms were examined and clustered. Moreover, applied platform strategies, process and task requirements for simple and intelligent RPA, and technical peculiarities were analysed. The results were clustered and listed into tables.

In a next step, the constructs and hypotheses of the within-case analysis were applied for a cross-case analysis across all RPA software providers. The analysis served to refine the constructs and to detect emergent patterns across RPA software tools. Subsequent interviews with RPA software integrators helped to confirm the general validity and applicability of the findings and to refine the framework.

In a last step, the resulting framework was further detailed by brief follow-up interviews with the RPA software providers. Thereby, critical assumptions were questioned, and information were refined to derive reliable results.

4.4 Classification and Analysis of RPA Software

The analysis of the conducted interviews and case studies based on a framework for cognitive intelligence (cf. Section 4.2.4) reveals two different approaches with regard to RPA and cognitive capabilities. The approaches are in line with past research (Plattfaut, 2019, van der Aalst et al., 2018, Wanner et al., 2019). On the one hand, RPA is defined as stand-alone software and any kind of cognitive intelligence is incorporated into the RPA software itself. This further development of RPA can be referred to as intelligent RPA and is detailed in Section 4.4.1. For the purpose of this research, all software that is defined as RPA without external solutions that are not incorporated into the software engine is regarded as intelligent RPA. On the other, features from cognitive intelligence can be combined with RPA using a platform approach. This means that the concept of simple RPA, as rule-based software, is not touched upon. The intelligence is added by external software, which is integrated into an RPA platform. The platform approach is detailed in Section 4.4.2. Academia and industry introduced the terms 'intelligent process automation' or 'intelligent automation' to specify this approach (Hofmann et al., 2019, Kokina and Blanchette, 2019).

4.4.1 Examination of Cognitive Intelligence within RPA Solutions

Based on the operationalised definition of cognitive intelligence, Table 4.2 provides an overview of identified elements of cognitive intelligence that are incorporated into intelligent RPA solutions.

They are derived from analyses of the conducted case studies. The RPA robots A to I correspond to the solutions of the software providers A to I, as introduced in Table 4.1.

Table 4.2: Overview of incorporated cognitive capabilities within RPA solutions.

Robot	Capture information			Process information		
	Text and character recognition	**Image recognition**	**Voice or sound recognition**	**Natural language processing**	**Machine learning**	**Automated reasoning**
RPA robot A	CR, KS	Basic OCR, CV	—	—	DC, TC, CV	—
RPA robot B	CR, KS	Basic OCR, CV	—	—	CV	—
RPA robot C	CR, KS	OCR, CV	—	—	DC, TC, CV, SH	—
RPA robot D	CR, KS	CV	—	—	CV	—
RPA robot E	CR, KS	Basic OCR, CV	—	—	CV	—
RPA robot F	CR, KS	Basic OCR	—	—	SH, RE	—
RPA robot G	CR, KS	CV	—	—	CV	—
RPA robot H	CR, KS	CV	—	—	CV	—
RPA robot I	CR, KS	—	—	—	—	—

Legend: CR = Character recognition, KS= Keyword search, OCR = Optical character recognition, CV = Computer vision, DC = Document classification, TC = Text classification, RE = Recommendation engine, SH = Machine learning-based scheduling

4.4.1.1 Capturing Information

Capturing information from digital text files with structured electronic text in the form of character recognition is regarded as a standard feature of RPA and included in all examined RPA solutions. Text files consist of structured electronic text that is separated by control characters such as line breaks or semicolons. The content is interpreted as sequence of characters from a set of characters. RPA can extract information from various formats of text files such as comma-separated values (CSV), extensible markup language (XML), or hypertext markup language (HTML) as well as from, for example, word processing programs, mail applications, or company information systems. The extraction of data from text files constitutes rule-based processing of information. It can be triggered either based on predefined rules within a process flow or based on events that are initiated by activities or keywords. RPA uses the events to release follow-up activities and succession processes. The robots, for example, copy text strings and transfer them into other systems, classify documents based on specific keywords, or use keywords to extract text information based on predefined rules. A typical example that occurred in various analysed RPA applications is the extraction of customer data from e-mails. Based on predefined rules, the robot from RPA provider H continuously monitors an assigned e-mail inbox. After receiving an e-mail, the robot reads out the text and searches for the keyword ‘account number’ or any other predefined customer related identification attribute. The attribute can also contain defined near-by words or cluster of words. If the e-mail contains the text-string 'account number', RPA is able to read out the following numeric symbols. Based on the identified string, RPA can attribute the e-mail to, for example, a client account logged in a customer relationship management system and forward the e-mail to the responsible human account manager. All activities are based on a clear rule set and require digital text files from assigned sources.

Optical character recognition (OCR) enables the extraction of text from images, ranging from scanned printed documents to pictures with text elements such as traffic signs. Five of the examined robots are able to process images, i.e. robots A, B, C, E, and F. However, most of them are limited to basic OCR capabilities and only one bot can perform advanced OCR per default. Basic OCR provides the ability to process scanned documents and convert the content into a structured digital text string. The incorporated technologies are limited to printed documents with a structured nature of text and printed fonts with a minimum density. Most of them rely on available open-source solutions that are integrated into the RPA engines. Only solution C contains advanced OCR capabilities. The OCR technology enables texts within images or tables, texts that are randomly located, or texts that are hand-written to be processed and transformed into structured output with a high level of quality. The majority, however, argue that OCR is a different technology then RPA and do not include OCR in their RPA solutions, as software provider D described:

> *We do not include OCR in our RPA solution, because we want to keep our solution flexible and the results predictable. For us, RPA is the execution engine that performs rule-based tasks. If a client wants to extract unstructured data, he needs to apply external software.*

To verify the basic OCR capabilities, a use case with robot B from the banking industry is analysed. After a new e-mail with scanned mortgage contracts arrives, the robot copies and saves the files on a local drive. In a next step, the robot converts the scanned text into a digital text string. After identifying the corresponding contract number based on a predefined keyword search, the robot uploads the text into a data management system and completes the process. Processing of scanned text with basic OCR is possible since the mortgage contracts follow predefined structures and are available as machine text.

Seven out of nine examined RPA solutions utilise computer vision technologies to identify, understand, and classify digital elements and objects on screens and user interfaces (robots A, B, C, D, E, G, H). The technology is based on similarity analyses and reacts to visual conformance. Computer windows and on-screen elements, such as buttons, can be identified and used as a trigger for process activities. Computer vision is regarded as an integral part of RPA and is used for applying RPA when underlying data cannot be accessed, as explained by provider E:

> *Computer vision is a core feature of RPA. Our strategy is to make the RPA engine just as intelligent as necessary to detect and process elements on the screen. The purpose is really RPA, which is why it is embedded.*

An example of how to apply computer vision is provided by RPA provider A. The robot is trained to search for the text string 'username' within a graphical, remote environment and uses it as anchor. The text box to the right of the text string is predefined as field to enter the username. Based on computer vision, RPA is able to identify the text string, detect the text field, and to insert the respective name.

Computer vision provides several advantages. First, the technology eliminates the reliance on selectors and underlying data, since it works with visible screen elements. It is even possible to use screen elements as anchors and access user interface elements, which are located within a certain distance. This enables a broader integration of elements and applicability. Second, the flexibility of RPA processes increases. Elements can be accessed even after modifications of software or changes in homepage designs. Third, computer vision enables remote automation on a virtual screen based on graphical data. This serves as fallback solution if other automation methods do not work.

None of the examined RPA solutions can process rich media, such as voice or sound. The technology is not regarded as an essential part of process automation with RPA, as RPA provider F commented:

> *Processing of rich media is complex and a di erent technology than RPA. It is not part of our solution, since we see enough demand on the text side. In addition, some of the tools and technologies in the market are not as robust as required yet. If you want to achieve a su cient accuracy level, it starts to get expensive. If required by a client, voice processing can be combined with RPA as third-party software.*

4.4.1.2 Processing Information

None of the examined RPA solutions contain incorporated NLP capabilities for contextual or sentiment analyses of texts. Only basic NLP features in the form of keyword search are included. However, keyword search is strictly rule-based and does not require any cognitive intelligence. In general, most RPA software providers do not regard NLP as a critical or core capability of RPA. To date, NLP is utilised as separate technology and integrated into RPA processes as a distinct component.

Two of the examined RPA robots provide built-in machine learning capabilities for document and text classification, i.e. robots A and C. In general, document classification enables the assignment of labels of a document type based on a predefined selection of options. The technology is based on supervised machine learning and combines different document properties, such as document type, author, subject, or content data to classify documents (Sebastiani, 2002). Document classification is an essential preliminary step for the efficient processing of data. After the document type is identified, specific text classification modules are applied. This enables critical information to be extracted and converted into structured output. The document and text classification modules are also based on supervised machine learning and trained by human employees. If a new invoice with an unknown design needs to be processed by RPA, the human employee first needs to assign certain elements like line-items, the total amount, or the invoice number on the document. Based on the allocation, the module learns and can independently classify all invoices of the same type. The integration of document and text classification capabilities correlates with the integration of basic or advanced OCR capabilities. However, there are only two RPA solutions with inherent basic and advanced OCR capabilities that include classification mechanisms. Most RPA software providers do not regard advanced OCR as part of RPA and rely on specialised, external third-party OCR software solutions. The software usually contains document and text classification capabilities, which is why they are not incorporated into RPA.

Computer vision, as described in Section 4.4.1.1, also contains machine learning features. First, OCR identifies keywords, which are used as anchors to define objects or text fields. Based on the shape and type of objects, machine learning is applied to determine the purpose and usage of objects. The algorithms are fed with a large amount of images and corresponding categories.

Also, error reporting in interaction with human users is used to further develop the machine learning algorithm.

In addition, supervised machine learning is applied by RPA vendor F for exception management in the form of an machine learning-based recommendation engine. The machine learning algorithm monitors exception handling activities of RPA users and learns based on their decisions. Thereby, changes on a code level or within workflows become superfluous, since RPA can automatically recommend configurations based on prior learnings and even perform them routinely. The examined use case contains a task, which includes the processing of scanned documents. In some cases, the characters 'O' and 'Q' look similar and cannot be assigned by the robot, which leads to an error. This requires a manual interference of a human user. The exception management algorithm monitors the solutions and recognises patterns. If it detects a similar exception multiple times, it makes a recommendation to the human user, and, after approval, routinely performs the exception. Since it improves the performance of RPA, it is regarded as useful for RPA and included in the software as an intelligent component. However, to date, no other provider offers a comparable solution.

Scheduling is a critical part of RPA, especially if multiple robots are applied or if one robot performs multiple tasks. The majority of RPA solutions use a scheduler based on predefined rules about the priority of tasks, the timing, or the duration of the execution. Two RPA providers offer built-in machine learning-based scheduling modules. They enable the dynamic scheduling of robots and tasks based on multiple parameters, such as scope and time requirements of tasks, defined service levels, concurrent processes, and the performance of underlying applications. The machine learning algorithm takes into account the defined parameters, the former performance of the robot, and the relation between latency times of applications and the resulting robot performance. Based on these input variables, the machine learning-based scheduler can automatically and dynamically schedule multiple robots to meet the agreed service levels. This enables flexible application and reassignment as well as increased service level fulfilment and utilisation.

None of the examined RPA solutions provide any kind of automated reasoning capabilities. The interview partners agreed that intelligence in the form of independent decision making should not be part of RPA. It weakens the ability of RPA to deliver accurate and predictable results based on explicit rules. RPA provider A distinguished between built-in intelligence in RPA solutions and intelligence outside the robot:

Automated reasoning is not the kind of intelligence that we want to build into RPA. It is an external intelligence that can be leveraged to answer questions or to carry out decisions. What RPA can do is the subsequent execution.

4.4.2 Enhancement of RPA with External Cognitive Intelligence

4.4.2.1 Introduction to Platform Approach

All nine examined RPA providers pursue the strategy of incorporating cognitive intelligence via a platform. This means that RPA, as a rule-based execution engine, is combined with selected external solutions. The external technologies are incorporated into the RPA platforms and can be easily integrated into the workflows as modules. RPA steers the cognitive components and executes the structured output. If needed, further external technologies can be added via application programming interfaces. Two levels of integration depth can be distinguished: on the one hand, providers completely separate RPA and cognitive intelligence, have no built-in capabilities within RPA, and leave RPA as rule-based execution engine (for example providers D, G, H, I). On the other, some providers integrate limited cognitive capabilities (for example providers A, B, C, E, F), as can be seen in Section 4.4.1. The level of intelligence is clearly limited and only technologies, which improve the core capabilities of RPA as execution engines, are incorporated.

The platform approach facilitates the integration of external technologies. This allows faster and more robust automation with little time required and no need for coding. The integration without coding is important in that it enables the application of RPA at a business level. By introducing a technology partner ecosystem and modular integration, RPA can be extended with best-in-class cognitive capabilities without the requirement for in-house solutions. This means that solutions from RPA providers, clients, or third parties can be leveraged and flexibility is increased.

4.4.2.2 Cognitive Intelligence within Platforms

Table 4.3 provides an overview of external cognitive capabilities integrated into the RPA platforms. Platform A corresponds to robot A, as introduced in Table 4.2. The digitisation of inputs by processing images via advanced OCR is identified as a standard feature of all nine

Table 4.3: Overview of cognitive capabilities integrated into RPA platforms.

	Capture information			Process information		
RPA platform	**Text and character recognition**	**Image recognition**	**Voice or sound recognition**	**Natural language processing**	**Machine learning**	**Automated reasoning**
Platform A	—	OCR	—	—	DC, TC	—
Platform B	—	OCR	—	—	DC, TC	—
Platform C	—	OCR	—	—	DC, TC	—
Platform D	—	OCR	—	NLP	DC, TC	—
Platform E	—	OCR	—	NLP	DC, TC	—
Platform F	—	OCR	—	—	DC, TC	—
Platform G	—	OCR	—	NLP	DC, TC	—
Platform H	—	OCR	—	NLP	DC, TC	—
Platform I	—	OCR	—	—	DC, TC	—

Legend: OCR = Optical character recognition, NLP = Natural language processing, DC = Document classification, TC = Text classification

RPA platforms. Most platforms offer OCR as module, which can seamlessly be integrated via drag-and-drop functionalities and convert data into structured input for the RPA engines. The providers include prepackaged leading external software solutions from suppliers, such as Abbyy or Kofax. In doing so, the RPA software providers can utilise best-in-class solutions to address specific digitisation problems and keep their RPA solution simple. In addition, some of the RPA platforms also provide interfaces to integrate open-source solutions on demand.

Four of the examined RPA platforms offer a built-in preselection of NLP solutions, which can be integrated via drag-and-drop as well (robots D, E, G, and H). The cases reveal that NLP is mainly used for contextual and sentiment analyses to understand the intent and body of texts and therewith increases the applicability of RPA. The platforms mainly originate from technology companies with competence in NLP and not from specialised RPA providers. The NLP software offered is either an internal solution or based on external software and, in any case, is not part of the license model. Even though it is regarded as a critical component, the majority of RPA platforms within the sample do not contain NLP capabilities as part of their platforms, as RPA software provider E emphasises:

> *Within RPA itself, there are no NLP capabilities yet and it is not a core functionality of our RPA platform. Nonetheless, some RPA processes include external NLP technologies based on license models or as open-source solutions to fulfil specific demands.*

As described in Section 4.4.1.2, RPA engines themselves partially provide supervised machine learning capabilities. With the platform approach, all examined solutions provide machine learning capabilities in the form of document and text classification. They are added through the integration of external OCR solutions, which have built-in document and text classification technologies. Moreover, all platforms enable the integration of additional machine learning solutions via standardised interfaces. For example, the programming language Python can be applied to code machine learning capabilities or to use pre-trained Python models for RPA. Thus, the RPA robot or platform itself does not include machine learning capabilities other than those described in Section 4.4.1.2, but it enables the integration of external solutions. Automated reasoning has not been part of any of the RPA platforms and examined cases.

To prove the described cognitive capabilities of RPA platforms, a case study in the field of client communication from an international financial institute has been analysed. The bank receives around one million e-mail requests each year, which need to be categorised and routed to employees for client service. The process causes a high manual effort, is prone to errors, and results in a long lead time for answering the requests. The applied RPA platform leverages an RPA engine, an OCR solution, as well as NLP to process the requests automatically. First, RPA receives the incoming e-mails as well as attachments and hands it over to OCR. The build-in OCR engine digitises the content and provides digital and structured data output. In a next step, NLP is applied to classify the content and categorise the e-mails. Based on the results, RPA takes over and routes the requests to responsible employees. For standard requests, RPA can even automatically generate responses and execute the requests. In addition, by escalating complex requests to human employees, the algorithm can learn and expand its capabilities.

4.4.3 Impact of Increasing Intelligence on Process and Task Suitability

The interviews confirm the key objectives for automating processes and tasks with simple RPA, as introduced in Section 4.2.1. Key drivers are increasing efficiency by reducing operational costs or execution time, improving the quality of output, and handling time critical or sensitive data. In addition, the identified criteria for process and task selection are in line with existing research (e.g. Bygstad, 2017, Lacity and Willcocks, 2016, Wanner et al., 2019). All experts highlight the requirement for clearly defined rules, a high degree of standardisation, and stable and mature processes with no or little exceptions as key decision criteria for simple RPA. In addition, processes and tasks require digital and structured data input and are particularly well suited for automation problems with multiple sources or interfaces. Most cases also cited a low automation rate as well as a low level of complexity as important. To achieve profitable cases, processes and tasks should be of medium to high volume and be at least repetitive and sequential in nature.

The increasing level of cognitive intelligence within RPA software solutions or as integrated solutions within RPA platforms impacts the applicability of RPA. According to the experts, the process requirement that is affected most is the need for structured data input, as intelligent RPA can work with unstructured or fast changing data. The data first needs to be transformed and structured by using OCR or NLP technologies. RPA subsequently receives the structured data and processes it based on predefined rules. Therewith, the requirement for structured data input decreases, although RPA still needs structured data to process tasks. RPA integrator E explains:

> *Unstructured data can be structured and made accessible based on intelligent RPA. The importance of standardisation of data decreases as the level of cognitive capabilities increases.*

Second, the requirement for a high degree of process standardisation as well as for clearly defined underlying rules decreases. Intelligent RPA can perform processes with changing process steps or rules. However, rules remain critical and an important prerequisite for RPA. So far, intelligent RPA can only perform changes or exceptions with low complexity. Third, the requirement for process stability becomes less important. Exception management based on a supervised machine learning algorithm enables the handling of errors and exceptions during the process or within unstructured data input. Nevertheless, the software solution still requires human employees for decision making as well as for processing of critical tasks. Even though this impact has been confirmed by most experts, only one examined RPA robot provides machine learning-based exception handling capabilities.

Regardless of the increasing cognitive capabilities that impact decision criteria for RPA, basic process requirements remain unaffected. A process that is structured, simple, and mature is still more eligible than a process with less structure and with exceptions. Cognitive capabilities broaden the field of application of RPA at the cost of complexity and implementation effort.

4.5 Discussion and Conclusion

4.5.1 RPA and Built-In Cognitive Intelligence

This research reveals that RPA has only very limited cognitive capabilities, despite the contrary being argued by software providers and indicated by research. Almost all experts from RPA providers as well as integrators emphasise that RPA is not intelligent and does not need intelligent capabilities. It is, as per definition, a software for the rule-based processing of click sequences with predictable and stable outcomes, which needs to be maintained. This has been confirmed by the interviews conducted and the analysis of nine RPA software solutions along a framework of cognitive intelligence. None of the RPA engines fulfil the prerequisites for cognitive intelligence and this therefore disproves the hypothesis of RPA being intelligent. Nevertheless, the research shows that all RPA solutions can process structured digital text and perform keyword search based on predefined rules. In addition, four of the examined RPA solutions have built-in basic OCR capabilities to process images in the form of scanned documents with structured text and one solution even provides advanced OCR. The findings are partially in line with prior research, which indicates that RPA is starting to get 'smart' features, such as image recognition (Hofmann et al., 2019, Plattfaut, 2019). However, the results reveal that the extent to which OCR is part of RPA is very limited and the majority of RPA software providers and integrators do not regard OCR as an essential part of RPA. Additionally, none of the solutions are able to capture complex, unstructured data input from sources such as voice or sound.

On the processing side, none of the RPA engines provide NLP or automated reasoning capabilities, which are core criteria for cognitive intelligence. They are regarded as complex and non-core technologies. According to the definition of cognitive intelligence, those components, however, would be critical to contribute machine intelligence to understand contextual meaning, reason, or draw conclusions (Gupta et al., 2018, Modha et al., 2011). Only the added value of machine learning is regarded as suitable to RPA. Therefore, machine learning in the form of supervised learning methods is incorporated in most of the examined RPA solutions, mainly through computer vision, document and text classification, and partially through scheduling and exception management. The findings confirm existing research, which indicates that learning capabilities should be incorporated into RPA solutions (van der Aalst et al., 2018, Wanner et al., 2019). However, the extent to which machine learning is used for RPA is limited. The cases emphasise that only machine learning capabilities enabling RPA to work more efficiently and expand its applicability without affecting the predictability and accuracy of outcomes are built into RPA engines.

The separation of RPA and cognitive capabilities as well as the consequential lack of intelligence of RPA relies on a broadly accepted rationale by the experts. First, the definition of RPA as a rule-based execution engine sets limits, which would be undermined by an unpredictable operation. Second, RPA provides the mechanical foundation for process automation, which is a key advantage. RPA should remain with exactly these capabilities, since the demand for rule-based automation is likely to continue to exist. Besides, it is the same with RPA as with human employees: building on basic requirements, companies recruit employees or train them to work on specific tasks. This flexibility can only be guaranteed with RPA if it remains an execution engine to which cognitive intelligence can be added flexibly. Third, most companies in the RPA market are RPA-only companies and have limited capabilities in the field of OCR, machine learning, or artificial intelligence. Since those technologies require a high degree of specialisation, it is reasonable to integrate best-in-class external technologies instead of developing proprietary solutions. The integration of non-RPA technologies also drives the complexity with regard to integration, usability, and maintenance with varying update cycles and technical requirements. Fourth, commercial restrictions hinder the incorporation of cognitive capabilities within RPA. The concept of modular RPA platforms enables the flexible tailoring of solutions to customer demands and reduces the costs for simple RPA.

4.5.2 Development Towards Platform-based Automation

All nine RPA providers offer RPA platforms to add cognitive intelligence to RPA as external elements. This indicates that the evolution of RPA towards more intelligent capabilities takes place based on external capabilities that can be bolted on to RPA in a modular fashion. The RPA software itself acts as execution engine within the platform, which steers external components and processes structured outputs. The case studies reveal that mainly OCR and NLP are added via the platform. As such, the key contribution comes with the ability to process information in the form of content understanding and supervised learning. Four RPA platforms provide preselected NLP solutions and all platforms enable the simple integration of external NLP technologies. However, RPA platforms still lack key cognitive capabilities, mainly in the field of automated reasoning. The experts cited a lack of transparency and reliability, the level of development of solutions with artificial intelligence, and the reluctance of users as the main reasons against the deployment of automated reasoning.

In general, the development towards RPA platforms is driven by the dynamic nature of most processes, which calls for flexible and non-static solutions. The modular platforms provide interfaces and an open architecture to external solutions. Since cognitive technologies are highly sophisticated and are developing rapidly, built-in capabilities would not be reasonable. Integrating intelligence via programming interfaces makes the platforms more robust and improves their operational efficiency and stability. The modular integration also ensures simple usability. This is vital, since RPA is applied on an operational business level and needs to be set up and operated by non-IT employees.

4.6 Limitations and Future Research

By following the principles for data validity as stated in the methodology section, this paper aimed to prevent structural errors. Nevertheless, the research is not without limitations. First, the definition and understanding of RPA potentially differs across software providers. Some regard RPA strictly as rule-based execution engine and refer to platforms for the integration of cognitive capabilities. In contrast, others refer to RPA as platforms, which combine RPA as rule-based engine with cognitive technologies. Even though this has been explicitly clarified during the interviews, a divergent understanding of RPA could have led to missing or exaggerated capabilities, which may reduce comparability. Second, the research is based on interviews and discussions on technical capabilities and concrete case documentations. However, it could make sense to further detail and specify the results by applying the RPA solutions on concrete and comparable use cases that require various intelligent features. The lack of access to the solutions of all included RPA providers impeded this approach. Third, the selection of RPA software providers is not exhaustive and is limited to the globally leading providers plus a selection of additional RPA companies. Even though the most important and market relevant solutions are included, the selection is not exhaustive. Fourth, the experts could have potentially overstated the actual capabilities of their RPA software and platforms. To overcome this problem, a bottom-up perspective from RPA integrators is introduced and case documentations are used to confirm the capabilities. Fifth, the applied analytical framework could potentially bias the results. However, core elements are included and no other features were detected during the interviews.

RPA and cognitive intelligence constitute interesting research opportunities. A general discussion about the definition and designation of RPA and cognitive intelligence would be needed to clarify the terminology used. This is important, since RPA is predefined and per definition rules out any kind of unpredictable or intelligence patterns. Potential new terminologies such as 'intelligent process automation' or 'intelligent automation' are already introduced and need to be further defined and detailed (Huang and Vasarhelyi, 2019, Kokina and Blanchette, 2019). Since this research provides indications of influences on process suitability, future research should address the question of how decision support criteria are affected by intelligent RPA. Another interesting research opportunity is the question of which cognitive capabilities complement RPA best and should be integrated to improve its applicability and efficiency. Moreover, research should address the implications of RPA with cognitive intelligence on its applicability within certain industries or business functions as well as the resulting effects on performance. Finally, research into the implications of cognitive intelligence and RPA on user acceptance and potential implementation challenges would be of interest.

5 Conclusion

5.1 Recapitulation of Research Findings

In recent years, RPA has grown into an important technology that complements the existing IT tool kit of corporations and widens the automation potential for processes and tasks that previously did not justify the use of traditional IT resources. In doing so, RPA liberates knowledge workers from performing mundane and repetitive tasks and enables corporations to focus their human resources on value-adding work. This dissertation enters the young field of research on RPA, which to date primarily consists of fundamental and exploratory case study research on the use of RPA from different perspectives. The aim of this dissertation is to examine RPA, as well as its applicability, based on three independent essays. In this regard, I want to contribute to a better theoretical understanding of the technology as well as of the applicability of RPA.

With my first essay in Chapter 2, I address the problem of process prioritisation in RPA projects. I present a structured approach for process selection consisting of the three steps goal definition, process identification and prioritisation, and process selection. To ensure that prioritisation remains quantifiable and objective, I introduce a mathematical model with formalised selection criteria based on empirically derived factor weights. Moreover, I demonstrate that a high degree of standardisation is the most important selection criterion and is followed by a high volume of transactions, a high level of maturity in processes and applications, a high degree of manual effort, digital and high-quality data input and a high failure rate. A test with real-life case data confirms the functionality of the model and reveals that it facilitates process selection in RPA projects and improves knowledge about the application of RPA. The proposed model is not without limitations. I intended to introduce a generally applicable model independent of industries or functions. Therefore, differences in the perceived importance of selection criteria are neglected and can potentially impact the results, depending on the application scenario.

Moreover, the criteria are not independent of each other and may possibly affect one another. A further weakness of the model is data collection, as it is manual and subject to human judgement. To solve the problem, I present possible solutions based on process mining. However, process mining is not included in the model. Besides the evaluation of the process suitability, economic factors may also impact process selection. Even though they are implicitly included in the model via selection criteria such as volume or standardisation that impact implementation effort, an economic assessment is not explicitly modelled.

In Chapter 3, I investigate the impact of RPA on management accounting as well as on the roles of management accountants. Based on case studies conducted with five case companies, I show that RPA is suitable for automating management accounting tasks and improves routinisation and efficiency. However, the overall impact is minor as management accounting lacks high-volume processes for automation with RPA. If compared to the introduction of ERPS in management accounting, I conclude that the impact of RPA is less and only affects a limited number of tasks with no impact on techniques. However, as RPA is a comparably new technology, the impact may increase in the future as adoption of RPA grows. Regarding the role of management accountants, I show that accountants become the customers of reporting data prepared by RPA. Therefore, they develop from an internal data and report generation role into a more analyst and consulting role and require enhanced technical knowledge. Overall, I present initial research on RPA and management accounting and lay the foundation for future work. However, it is not without limitations. Reported findings on the applicability of RPA, changes in techniques and organisational implications may change as firms gain more experience with RPA, which is still in its infancy and only applied by a few companies. The interview-based approach could also have led to an overstatement of RPA capabilities, which I tried to mitigate by including process documentations, cost calculations and other reports. Moreover, the case selection is not exhaustive and does not include any companies that use RPA extensively across all possible fields of application. As I was not able to identify any such companies after extensive research, I assume that this is because RPA utilisation is still in an early stage. The latter also impeded a longitudinal study, which is why data collection took place during a limited period of two months.

With essay III in Chapter 4, I complement the existing literature by investigating the effects of the integration of artificial intelligence technologies on the capabilities and the applicability of RPA. I find that RPA has only very limited cognitive capabilities and disprove the hypothesis of RPA being intelligent. In particular, I show that only intelligent capabilities in the form of capturing unstructured information and supervised learning are incorporated into RPA. The limited integrated intelligence can be explained by the rule-based nature of RPA, the need for predictability of results and the complexity and early stage of artificial intelligence technologies. I also introduce a platform approach, with which intelligent capabilities can be combined with RPA in a modular fashion. In addition to the results of essay I, I show that intelligence impacts the applicability of RPA and broadens its field of application. In particular, the need for standardisation, process stability and structured data input decreases. Also, the results of essay III are subject to limitations. First, a divergent understanding and definition of RPA between the interview partners could have led to missing or exaggerated capabilities, which may reduce comparability. Second, only data from interviews and documentations are included. Data from an application of RPA to concrete use cases could have helped to increase comparability, but not all software was accessible. Third, the selection of cases is not exhaustive, but is intended to cover the most important global providers and market relevant solutions. Fourth, potential overstatements of RPA capabilities by the experts consulted cannot be ruled out, although bottom-up validations from RPA integrators are introduced to mitigate the effect. Fifth, the applied analytical framework could potentially bias the results. Nevertheless, no evidence of this was found during the interviews.

5.2 Directions for Future Research

Based on the findings from the three essays as well as the accompanying limitations, many exciting research opportunities arise, which are strengthened by the dynamic development of RPA technologies. The results of essay III reveal that the interplay between RPA and artificial intelligence technologies constitutes an important avenue for the future development of RPA. As research on the issue is still in its infancy, there are many questions in need of further investigation. With regard to the applicability of RPA, I indicate that the need for standardisation, maturity, and structured data input is affected by RPA becoming more intelligent. Since I am not analysing the implications in detail, future research should address the question of how intelligent technologies impact the applicability of RPA as well as process selection criteria and factor weights. Moreover, I show that machine learning technologies enable RPA to learn and to self-reconfigure based on its experience from operations. As the degree of machine learning capabilities of RPA is still limited, future research should examine the question of how to let

RPA agents learn and how to train RPA agents. Furthermore, all essays show that deviations from predefined rules and exceptions constitute a major obstacle for RPA. Therefore, research on seamless handling of exceptions and exception handling architectures needs to be intensified. Innovative approaches and technologies could also be used to further optimise and automate the proposed process selection model from essay I, as process identification and data collection is manual and cumbersome. Therefore, research on the integration of intelligent methods, such as process or task mining, to support the automated discovery of candidate processes would provide an interesting opportunity for future scholarly work.

In addition to process identification and implementation, an organisational view of RPA projects as well as organisational readiness is of interest and currently lacking research. Therefore, I propose further examining the impact of RPA on organisational strategies, governance and management systems in order to establish RPA as a sustainable automation instrument. In addition, there is a lack of knowledge about the degree of organisational readiness for RPA, as well as about resources required to prepare for an effective RPA implementation. Here, research work could provide support by developing readiness or maturity assessment frameworks to assist organisations in effectively utilising RPA.

Considering a human labour perspective, I show that the roles of management accountants are changing as are the skills required. For example, skills relating to process management, exception analysis and robotic software development as well as operation need to be improved. At the same time, employees' insecurities when working alongside robots are increasing. These findings can be generalised to the overall deployment of RPA, and the resulting implications on the workforce need to be better understood. This is also indicated by existing literature on the topic (e.g. Dias et al., 2019, Stock et al., 2019, Syed et al., 2020). Therefore, I suggest that future research should investigate human-robot interactions and how humans and robots can work together seamlessly. This can also help to examine the impact of RPA on the human workforce as well as changes to employee roles that are most prone to automation. In this context, it would also be interesting to see more research on the level of trust by employees and management in the work of RPA and the outcomes of automated tasks. From a governance perspective, implications of RPA on IT or human resources policies, as well as on change management, constitute an important future field of research.

5.3 Concluding Remarks

The results of this dissertation represent an important contribution to the literature on RPA. On the basis of three essays, I provide new knowledge about crucial determinants to select the most suitable candidate processes for automation with RPA, expand the research about the applicability and impact of RPA on management accounting as an untapped field of knowledge and lay the foundation for future research on the compatibility of RPA and artificial intelligence technologies. As RPA constitutes a comparably young field of research, I mainly apply qualitative and exploratory research methods to address the research questions. Overall, I show that RPA is well suited for automating back office tasks and therefore provides a suitable means of expanding the robotisation wave from direct into indirect corporate functions. However, as indicated by existing research (e.g. Lacity and Willcocks, 2016, van der Aalst et al., 2018) and confirmed by the findings of this dissertation, the technology is only applicable to rule-based and simple tasks. To overcome this limitation, I show that combining RPA with artificial intelligence technologies for information capturing and processing extends its applicability to more complex and unstructured tasks, although this is still at an early stage.

This dissertation yields important overarching contributions, which result from the three essays and connect the research findings of all essays. First, I contribute to the emerging research on process selection problems in RPA projects (e.g. Osmundsen et al., 2019, Santos et al., 2019, Wanner et al., 2019). To date, the selection has mainly been discussed through case studies in specific fields of application, but no generalisable models have been presented. To the best of my knowledge, this research is the first to present a generalisable and quantifiable method for prioritising candidate processes to improve process selection in RPA projects based on empirically derived factor weights. In addition, I show that artificial intelligence technologies impact process selection criteria and expand the field of application of RPA. The findings can further reduce failure costs and improve the utilisation of resources in RPA projects. Second, I supplement the generalisable selection model by examining the specific potential for process automation with RPA in management accounting. I make an important contribution by entering an untapped field of research, and expand existing knowledge about the application potential of RPA from auditing and accounting to management accounting. I conclude that RPA impacts both management accounting and the role of management accountants, however, so far only with minor effect. Third, this dissertation is one of the first works to combine the two fields of research on RPA as well as on artificial intelligence technologies. I address the fundamental question of the extent to which artificial intelligence is necessary for RPA and to which it makes sense to combine the two concepts. With this, I lay the foundation for further research and clearly differentiate RPA from artificial intelligence. By introducing an examination framework for intelligent capabilities, I demonstrate that RPA has only limited intelligent capabilities and that intelligence should be added modularly via a platform approach.

The results of the essays bear several important practical implications for RPA developers as well as end users in industry. The dissertation provides guidance for the selection of promising RPA process candidates, for both rule-based and intelligent RPA. Specifically, the proposed quantification of the process suitability guides executives towards selecting the most promising process candidates. As a result, the overall efficiency in process identification can be increased, the probability of RPA project success grows and failure costs can be avoided. Besides general applicability, the results pave the way for corporate executives to leverage RPA in management accounting. The task-specific application potential introduced, as well as the benefits that result, guide the identification of candidate tasks for RPA and enable a critical review of tasks that have already been automated. As RPA is identified as impacting the job profiles of management accountants, the results of this dissertation can also help to adapt the training and hiring criteria for management accountants. Moreover, the findings suggest detailed intelligent capabilities that are beneficial for RPA, as well as an approach to integrating and combining them with RPA software. This supports RPA developers in future technological developments to improve the overall capabilities of RPA. In addition, it informs applicants about the potential of combining artificial intelligence technologies and RPA, and can thus extend the utilisation of RPA.

In conclusion, the findings of this dissertation confirm the introductory quote by Sabine Hauert for the application of RPA (Lewis, 2017). After physical robots have taken over dangerous and demanding tasks in operations, RPA represents the next step in robotisation by automating knowledge workers' tasks and thereby releasing them from demeaning and dull duties. As a result, RPA enables humans to focus on value-adding tasks that require critical thinking and human creativity. Moreover, RPA expands the automation potential to tasks that previously did not justify automation with complex and costly heavyweight IT, as RPA is a flexible, lightweight solution that can be set up at a business level. The findings of this dissertation suggest that RPA strongly impacts the work and role of knowledge workers, which has the potential to change tomorrow's working world. As RPA constitutes a young field of research and is developing at a fast pace, it offers manifold interesting research opportunities as presented in this dissertation and beyond.

Appendix

Appendix to Essay I

Table A.1 provides an overview of the interview guidelines with detailed interview questions for essay I. The interviews were semi-structured and consisted of three parts: (1) an introduction into the companies' experience with RPA and the capabilities of the RPA solutions provided, (2) a reflection on key motivators for the implementation of RPA as well as resulting benefits, and (3) a discussion of process selection approaches and criteria.

TABLE A.1:
List of interview questions for essay I.

Structure	Interview questions
General information	What is your current role? How long have you been dealing with RPA and how experienced are you in RPA? What is your company's background? Why and since when have you been using RPA and how have you organised your RPA initiatives? What RPA software do you use?
Motivation for RPA	Which processes have you already automated using RPA and what motivated you to apply RPA for each process? How do you decide whether to use RPA or traditional BPM solutions? What indicators do you use to assess the economic return of RPA projects? What qualitative and quantitative benefits resulted from automation with RPA?
Process selection	How do you identify new processes? How do you assess the automation potential of RPA processes? Which processes are best suited to be automated with RPA? What are the most important characteristics that processes need to fulfil in order to be ideal RPA candidates? Do you automate processes without adjustment or do you first streamline the processes before their implementation? How does intelligent RPA impact the criteria and the applicability of RPA?

Table A.2 presents the results of the conducted linear regression analysis with experience as a fixed effect and all identified process selection criteria as dependent variables. Control variables include indicator variables for the level of motivation to apply RPA and the type of company where the interviewees are employed. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2:
Linear regression analysis.

	Dependent variables							
	Standardisation	Maturity	Failure rate	Volume	Manual effort	Number of interfaces	Digital data input	Structured data input
Experience	-0.049*** (0.021)	-0.012 (0.018)	0.024 (0.019)	0.017 (0.018)	-0.023 (0.015)	0.000 (0.012)	0.027 (0.018)	0.017 (0.018)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES	YES	YES
N	134	134	134	134	134	134	134	134
Pseudo R^2	0.098	0.065	0.136	0.165	0.209	0.083	0.096	0.091

Table A.3 provides summary statistics derived from the conducted survey for each of the identified process selection criteria. We report mean and median significance tests. The difference in means is estimated by a paired t-test (t) for means. The difference in medians is estimated by a nonparametric Wilcoxon signed-rank test (z) for unreported medians. We report t-values for the difference in mean tests and z-values for the differences in median tests. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE A.3:
T-test and z-test.

	Dependent variables							
	Standardisation	Maturity	Failure rate	Volume	Manual effort	Number of interfaces	Digital data input	Structured data input
Mean	0.192	0.124	0.105	0.147	0.127	0.083	0.112	0.110
Median	0.182	0.102	0.080	0.118	0.111	0.068	0.083	0.086
Standardisation								
t-test		7.228***	7.226***	3.392***	4.625***	9.399***	5.618***	6.130***
z-test		6.619***	6.642***	3.390***	4.343***	7.441***	5.130***	5.627***
Maturity								
t-test			1.949*	-1.739	-0.268	4.270***	0.790	1.133
z-test			2.657***	-1.493	0.107	4.285***	0.965	0.950
Failure rate								
t-test				-3.487***	-1.872*	2.204**	-0.755	-0.466
z-test				-3.395***	-1.884*	1.764*	-0.769	-0.944
Volume								
t-test					2.182**	6.143***	2.681***	3.172***
z-test					3.273***	5.528***	3.054***	2.970***
Manual effort								
t-test						3.919***	1.194	1.587
z-test						3.445***	1.781*	1.700*
Number of interfaces								
t-test							-2.832***	-2.451**
z-test							-1.726*	-2.288**
Digital data input								
t-test								0.591
z-test								1.084

The following Figures A.1 to A.7 provide an overview of the suitability values (y-axis) for the RPA process candidates examined from an exemplary management accounting function for each of the seven selection criteria. The processes are denoted as follows: validation of stock (P1), calculation of material configurations (P2), intercompany revenue clearing (P3), intercompany revenue elimination for a specific product (P4), material price maintenance (P5), month-end closing (P6), warranty provisions (P7), intercompany revenue elimination (P8) and lowest value determination (P9).

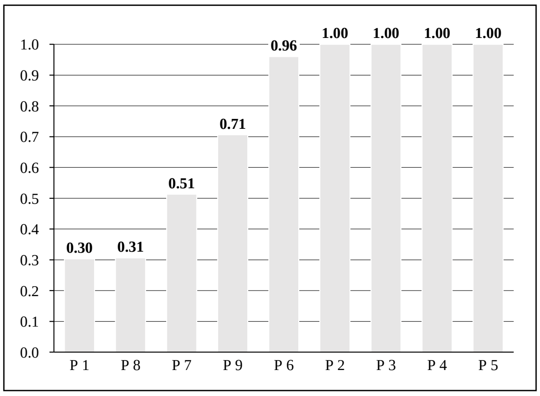

FIGURE A.1: Overview of suitability values for the criterion ‘standardisation’.

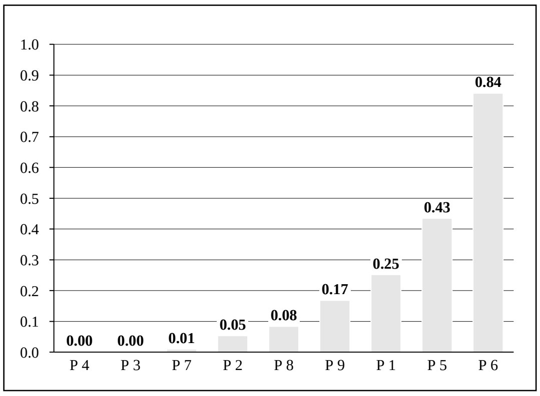

FIGURE A.2: Overview of suitability values for the criterion ‘volume’.

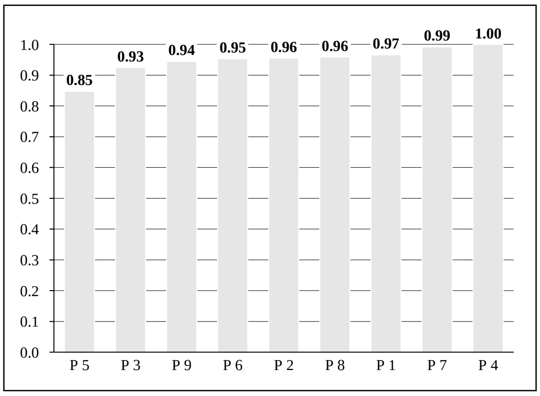

FIGURE A.3: Overview of suitability values for the criterion ‘manual effort’.

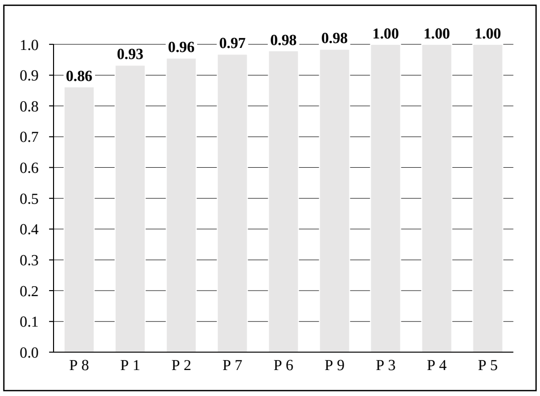

FIGURE A.4: Overview of suitability values for the criterion ‘maturity’.

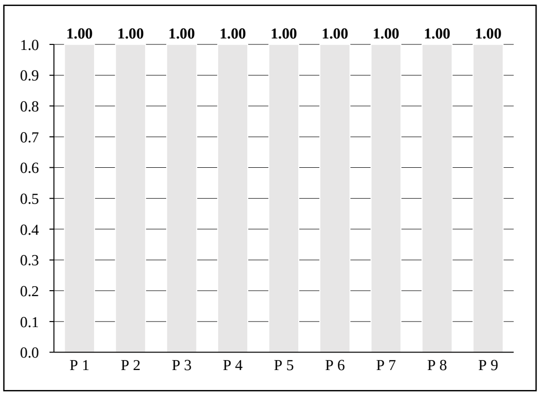

FIGURE A.5: Overview of suitability values for the criterion 'digital data input'.

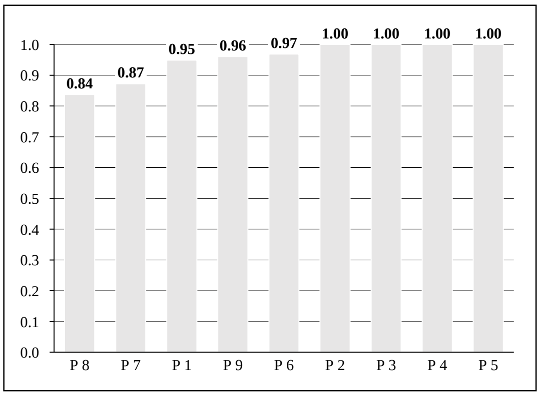

FIGURE A.6: Overview of suitability values for the criterion 'structured data input'.

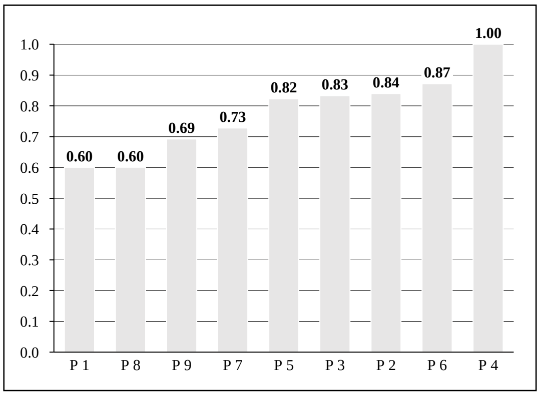

FIGURE A.7: Overview of suitability values for the criterion 'failure rate'.

Appendix to Essay II

Table A.4 gives an overview of the interview questionnaire as well as the detailed questions discussed when conducting the semi-structured interviews for essay II. The interviews were structured into three parts. First, general information about the RPA organisation as well as the maturity of RPA implementation were discussed. Second, all automated management accounting processes, their identification, the resulting benefits, and occurring challenges were enquired in detail. Third, potential implications on management accounting as well as on management control were discussed.

Table A.4:
List of interview questions for essay II.

Structure	Interview questions
General information	What is your current role? Since when are you dealing with RPA and how experienced are you with RPA? Since when are you applying RPA and what was your motivation? How have you organised your RPA initiatives? How do you identify new processes? How did your system landscape evolve and what systems are you using?
Application of RPA	Which management accounting processes have you automated with RPA? What makes management accounting processes suitable for RPA? Based on which criteria have you selected the processes? What drove the automation and what are key qualitative and quantitative benefits? What are major issues and challenges for implementing and operating RPA? Are additional processes planned to be automated with RPA? Limitations of RPA in management accounting?
Management accounting	To what extent does RPA change management accounting tasks? To what extent does RPA lead to changes to management accounting techniques used by your firm? To what extent does RPA impact key performance indicators? How did standardisation, speed, detail, and accuracy change? Is a more timely and strategic management accounting possible? To what extent does RPA lead to changes to the organisation and management accounting roles? To what extent does RPA lead to changes to the entire organisation and management control?

Appendix to Essay III

Table A.5 gives an overview of the interview questionnaire as well as the detailed questions discussed when conducting the semi-structured interviews for essay III. The script followed the recommendations by Myers and Newman (2007). The first part covered the informants background, current role, and experience with RPA as well as a detailed overview on the companies' history and development. The second part focused on the companies' RPA offering with regard to intelligent capabilities as well as key technology limitations. The third part targeted process and task characteristics required for simple as well as for intelligent RPA.

Table A.5:
List of interview questions for essay III.

Structure	**Interview questions**
General information	What is your current role? What is your company's background? Since when are you dealing with RPA and how experienced are you with RPA? Why and since when are you using RPA and how have you organised your RPA initiatives? Which RPA software are you applying?
Intelligent RPA	How do you define RPA? What does intelligent RPA mean to you? How would you describe the current status of intelligent RPA? What are the key capabilities of intelligent RPA solutions, which are used for the automation of back office tasks? According to your experience, is RPA able to process language, represent knowledge, reason, and learn based on machine learning and which technologies are used? Can you please give concrete examples of processes/tasks and solutions that have been implemented with intelligent RPA solutions? In which stadium are the features and capabilities? What are key improvements and differences compared to rule-based RPA? Which of the technologies are integrated and which are external? What are pros and cons of integrated solutions versus externally provided solutions? What are the greatest challenges in developing AI based RPA solutions? What are key limitations of RPA with becoming intelligent? How and in what direction will the technology develop in the future? Will RPA become an automation platform which includes, connects and combines various technologies to achieve and end-to-end automation?
Process requirements	How does AI influence the process requirements and characteristics required for the implementation of intelligent RPA solutions? What are the most important process characteristics? Which criteria become more or less important versus rule-based RPA and why?

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