Technische Universität München
TUM School of Management

Towards a Configurational Perspective on Team-Based Innovation

Niklas Christoffer Hagenow

Vollständiger Abdruck der von der TUM School of Management der Technischen Universität München zur Erlangung eines

Doktors der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.)

genehmigten Dissertation.

Vorsitz: Prof. Amy Zhao-Ding, Ph.D.

Prüfende der Dissertation:

1. Prof. Siddharth Vedula, Ph.D.
2. Prof. Dr. Johannes Meuer

Die Dissertation wurde am 07.01.2025 bei der Technischen Universität München eingereicht und durch die TUM School of Management am 15.03.2025 angenommen.

Acknowledgements

First, I extend my deepest gratitude to Prof. Siddharth Vedula, PhD and Prof. Dr. Claudia Doblinger for their invaluable guidance throughout my dissertation journey. I am sincerely grateful for their support in navigating the complexities of the doctoral process. Sid, your optimism was a constant source of strength, recharging my determination during challenging times when setbacks and non-findings could have easily undermined my motivation. Claudia, I am deeply thankful for your expertise and continual insights, without which my work could not have reached its present standard.

I would also like to express my heartfelt thanks to my dissertation committee members, Prof. Amy Zhao-Ding, PhD and Prof. Dr. Johannes Meuer. I am grateful to Amy for laying a solid foundation for my studies through her PhD seminar on organizational theory. This seminar introduced me to a broad array of scholarly work and equipped me with a toolbox that has been indispensable throughout my PhD journey. To Johannes, thank you for your time, careful review, and the methodological guidance you provided.

I am also grateful for the opportunities to engage with the QCA community in various settings. The QCA paper development workshops organized by the COMPASSS network and the EGOS subtheme coordinated by Johannes have been tremendously insightful. In this context, I would like to express my special appreciation to Prof. Peer Fiss, PhD, whose guidance has been exceptionally fruitful and has profoundly shaped my research.

I would also like to extend my heartfelt thanks to Prof. Dr. Mirjam Knockaert and the wonderful team at Ghent University for welcoming me as a visiting researcher. Your academic environment truly became a second academic home for me, and the insightful exchanges with each of you made a meaningful contribution to my growth as a researcher.

My time at the ERI was enriched by the talented and supportive colleagues I had the pleasure of working alongside, whose warmth and encouragement brought both depth and enjoyment to my academic journey. I am especially grateful to Madeleine Kutschbach for her exceptional administrative support. I would also like to thank the professors and fellow doctoral students for their valuable feedback on my research and for their inspiring insights into academia.

Finally, I am endlessly grateful to my family and friends for their unwavering love and support. This journey did not just start with my PhD – it began long ago with the encouragement, sacrifices, and belief of those closest to me. You made every step possible, standing by me through moments I never thought I would overcome. I know how rare it is to have such incredible people to lean on when things get tough, and I never take that for granted. You know who you are, and I could not have done this without you.

Munich, December 2024

Contents

List of Figures

List of Tables

Abbreviations

CPC	Cooperative Patent Classification
EGOS	European Group for Organizational Studies
EPO	European Patent Office
IEA	International Energy Agency
IPC	International Patent Classification
IPCC	Intergovernmental Panel on Climate Change
MNE	Multinational Enterprise
PDW	Paper Development Workshop
PI	Principal Investigator
PoC	Proof of Concept
PV	Photovoltaic (Energy)
QCA	Qualitative Comparative Analysis
R&D	Research and Development
SME	Small and Medium-Sized Enterprises
TMT	Top Management Team
USPTO	United States Patent and Trademark Office
WIPO	World Intellectual Property Organization
WoS	Web of Science

Outcome and Condition Abbreviations

DEG	Degree Centrality / Central Network Position
DOM	Domain Experience
ETHN	Ethnic Diversity
GATE	Gatekeeper
GEO	Geographic Dispersion
GEND	Gender Diversity
GEXP	General Experience
GNRL	Generalist
IMPACT_INNO	Impactful Innovation
INST	Institutional Diversity
KNOW_DIS	Knowledge Dissimilarity
KNOW_VAR	Knowledge Variety
MOB	Inventor Mobility
ORG	Organizational Diversity
PGAP	Prestige Gap
PRICOL	Prior Collaboration
RECOMB	Recombination Novelty
SIZE	Team Size
STAR	Star Inventor

Abstract

This dissertation adopts a configurational perspective to explore how innovation team composition influences innovation outcomes. As technological complexity continues to grow, innovations increasingly emerge from collaborative efforts by teams of multiple inventors. While prior research has examined various individual factors of team composition, the intricate interplay of multiple factors remains underexplored. To address this gap, this dissertation first synthesizes existing research on innovation team composition. Given the theoretical ambiguity surrounding the relative importance of the diverse factors studied in the literature, I propose a novel data-driven approach to identify the most central factors for a subsequent set-theoretic analysis. Using Qualitative Comparative Analysis (QCA), I reveal team configurations linked to particularly impactful innovations that shape the technological trajectory in their domain, focusing on a comprehensive dataset of patented inventions in the clean energy sector as a topical study context. The findings highlight the significance of continuity in collaboration and the role of deep domain expertise. These insights offer guidance to policymakers for designing effective strategies to foster innovations that address grand societal challenges, such as climate change, while also directing scholars toward promising avenues for future research.

Zusammenfassung

Diese Dissertation verfolgt eine konfigurative Perspektive, um den Einfluss der Teamzusammensetzung auf Innovationsergebnisse zu untersuchen. Mit der zunehmenden Komplexität technologischer Entwicklungen werden Innovationen immer häufiger das Ergebnis kollaborativer Anstrengungen von Teams aus mehreren Entwickler:innen. Während sich die bestehende Literatur bereits umfassend mit einzelnen Faktoren der Teamzusammensetzung beschäftigt hat, wurde dem kausal komplexen Zusammenspiel mehrerer Faktoren bislang nur wenig Aufmerksamkeit geschenkt. Um diese Forschungslücke zu schließen, wird zunächst eine Bestandsaufnahme des aktuellen Forschungsstands vorgenommen. Da frühere Studien nur begrenzt Aufschluss über die relative Bedeutung verschiedener Faktoren geben, entwickle ich in dieser Arbeit einen datengetriebenen Ansatz, der es ermöglicht, die zentralen Faktoren der Teamzusammensetzung zu identifizieren. Anschließend führe ich basierend auf einem umfangreichen Datensatz von Patenten aus dem Bereich emissionsfreier Energietechnologien eine set-theoretische Analyse durch, die aufzeigt, welche Teamkonfigurationen mit Innovationen verbunden sind, die einen besonders großen Einfluss auf die weitere technologische Entwicklung haben. Die Ergebnisse zeigen, dass insbesondere die Kontinuität in der Zusammenarbeit mit denselben Teammitgliedern sowie ein hohes Maß an domänenspezifischem Wissen entscheidend für solche bahnbrechenden Innovationen sind. Diese Erkenntnisse bieten Entscheidungsträger:innen und Akteur:innen in Forschung und Entwicklung wertvolle Ansätze, um den technologischen Herausforderungen unserer Zeit wirksam zu begegnen.

1. Introduction

"My basic optimism about climate change comes from my belief in innovation. The conditions have never been more clear for backing energy breakthroughs. It's our power to invent that makes me hopeful."

– Bill Gates (2022) - breakthroughenergy.org

1.1 The Global Climate Emergency and the Role of Innovation

Anthropogenic climate change is an undisputable threat to us and our planet (Hodson, 2017; IPCC, 2022). Projected consequences include, but are not limited to, the disruption of entire ecosystems, water scarcity and threats to food security, loss of lives and destruction of infrastructure due to more severe and more frequent weather extremes as well as the displacement of humans from exceptionally vulnerable regions (IPCC, 2022).

As summarized in the latest synthesis report by the *Intergovernmental Panel on Climate Change* (IPCC, 2023), it is a scientific consensus that the ongoing rise in global surface temperatures is attributed to the expansive emission of greenhouse gases from human activities since the 19th century. A global industrial system reliant on fossil fuel combustion for energy production is the root cause of extensive carbon dioxide emissions into the atmosphere (IPCC, 2023). While these unsustainable practices have already caused the energy sector to be the largest contributor to cumulative greenhouse gas emissions, and thus climate change, it remains one of the economic sectors with the largest growth in emissions to this day.

In 2021, the *International Energy Agency (IEA)* published a roadmap document with key recommendations directed towards policymakers "for what needs to happen […] to transform the global economy from one dominated by fossil fuels into one powered predominantly by renewable energy" (IEA, 2021, p. 3). The report lays out a path to net zero emissions in the energy sector by 2050 while "addressing energy security and affordability concerns" (IEA, 2022, p. 119). Although the outlined net zero scenario acknowledges that a variety of clean energy solutions, such as hydropower, bio-, geothermal, and photovoltaic (PV) energy, have already reached a mature state and need to be deployed on a larger scale, the limited remaining time frame to reach net zero emissions requires us to develop other key building blocks such as advanced energy storage, hydrogen technologies, and biofuels at an unprecedented pace. “Bringing early-stage clean energy technologies to market by 2030[1] requires going from first prototype to market around 20% faster on average than the quickest energy technology developments in the past, and around 40% faster than was the case for solar PV” (IEA, 2022, p. 230). Since especially such early-stage technologies often fail to attract the required funds from the private sector due to large investment volumes at relatively high risks, effective public investments in such innovation projects reflect a cornerstone for a successful shift of energy production, distribution, and storage to more sustainable practices. Hence, despite the seemingly ample timeframe to 2050, the IEA calls for immediate action for the outlined net zero scenario to be achievable. Yet, after another two years of record high emissions in 2021 and 2022 primarily attributed to “extraordinarily rapid post-pandemic economic growth” (IEA, 2022, p. 121), investments into new fossil fuel projects after Russia’s invasion of Ukraine (IEA, 2023), and slow progress in the sustainable transformation of energy systems, the IEA quickly released a fully updated roadmap document in 2023. While admonishing that – considering the “mostly discouraging developments” (IEA, 2022, p. 121) – the “pathway detailed in the […][scenario] remains narrow” (IEA, 2022, p. 121), the update also points to recent successes: The deployment of photovoltaic systems is ahead of the projection provided in the original net zero scenario and the advancements as well as cost reduction for batteries have been a driver for the urgently needed electrification in some domains. Nevertheless, innovation progress remains too slow for some crucial areas such as hydrogen technology, floating offshore wind power, low-emission jet fuels, or carbon capture technologies. Overall,

[1] 2030 is a key milestone in the IEA’s net zero by 2050 scenario.

approximately 35% of the technologies essential for achieving net zero emissions in the energy sector by 2050 still require significant advancements (IEA, 2023).

For the outlined reasons, I use the clean energy sector as a topical context for this dissertation. With my research, I seek to enhance our understanding of where the impactful innovations we urgently require come from and thus equip policymakers with insights that can inform their decision-making to design policy strategies and direct resources more effectively to where technological progress is most likely to be created. In the following sections, I discuss how the most impactful innovations – those that serve as foundational building blocks for subsequent advancements – are increasingly the result of collaborative research performed by teams. More specifically, I highlight the need for a *configurational perspective* – one that examines the complex interplay of multiple conjunctural team composition factors – on team-based innovation and detail the key research objectives for this dissertation.

1.2 The Trend Towards Team-Based Innovation

While rapid advancements rather than incremental improvements in the development of clean energy technologies are fundamentally necessary to reach the sector's emission goals, significant technological progress has become increasingly difficult to achieve (Jones, 2009; M. Park et al., 2023). The share of major innovations that substantially changed the trajectories within and across fields, and thus led to a shift in technological boundaries (Dosi, 1982), has been on the decline (M. Park et al., 2023). While some scholars (e.g., Cowen, 2011; M. Park et al., 2023) argue that this trend points to an exhaustion in the exploitation of "low-hanging-fruits" (M. Park et al., 2023, p. 138) – developments that are relatively easy to accomplish – other scholars suggest that it is the increasing complexity of technologies that results in a "burden of knowledge", making it more challenging for scientists to reach the frontier of their field (Jones, 2009).

With a growing knowledge stock, and as more knowledge is accumulated within individual technological developments over time, scholars have argued that innovations increasingly rely on collaborative efforts among inventors with diverse knowledge backgrounds from narrower fields of expertise (Jones, 2009; Wuchty et al., 2007). Studies have shown that collaborative research is consistently outperforming the work of solo authors across all scientific fields. Not only did the share of research produced by teams constantly increase over the last decades, but so did the average size of the teams that conducted the research (Jones, 2009; Wuchty et al., 2007). The advantage of collaborative teams has also been demonstrated in the specific context of technological innovation. For example, Singh and Fleming (2010, p. 41) show that collaboration "reduces the probability of very poor outcomes […] while simultaneously increasing the probability of extremely successful outcomes". In line with the broader trend, the clean energy sector has likewise experienced a significant shift towards collaborative innovation (Figure 1.1) – a reasonable approach for clean technologies as their "systemic, credence and complex character […] suggest[s] that, to develop them, cooperation may be even more important than when it comes to [the introduction of] other types of innovations" (De Marchi, 2012, p. 615). Furthermore, in recent years, policymakers have aligned with this pattern and formed multilateral initiatives, such as the global *Mission Innovation* initiative or the European Union's *Horizon Europe* program, to accelerate the development of clean energy technologies. These initiatives foster the pooling of resources and expertise and encourage a collaborative approach to clean energy innovation.

1.3 Understanding Successful Innovation Teams

As the most influential innovations increasingly result from collaborative efforts within teams of scientists, researchers have sought to better understand the *team-level antecedents* of successful innovation and, more specifically, to identify the *contributing factors* that foster outstanding innovation outcomes. For instance, early research by MacCormack et al. (2001)

investigates the impact of team members' *prior experience* in the focal domain on the quality of newly developed technical products; Gay et al. (2008) find that having an inventor with *exceptional past performance* or a *foreign inventor* on the team positively impacts the value of an invention; Bercovitz and Feldman (2011) explore various predictors of successful team-based innovation, including *prior collaborations* among team members, their *organizational affiliations*, *job function diversity*, *institutional backgrounds*, and *geographical factors*. More recently, scholars have also focused on the factors specifically contributing to "green" innovations. Studies indicate that drawing on different perspectives from team members with *diverse ethnic backgrounds* (Marino & Quatraro, 2022) or *varied knowledge bases* (Orsatti et al., 2020) can facilitate the development of "environmentally sound technologies" (WIPO, 2024).

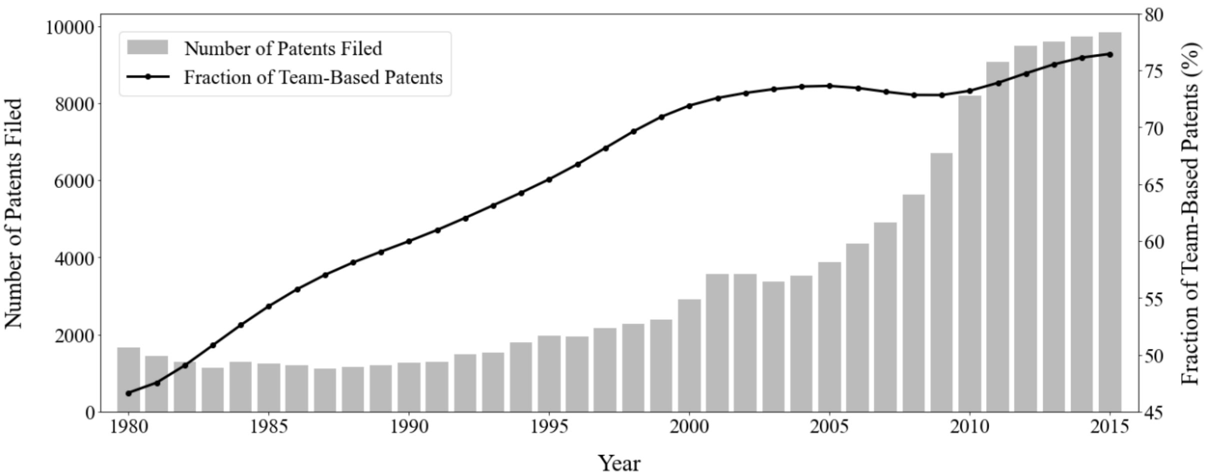


Figure 1.1: Number of clean energy patents filed per year and fraction of team-based patents.[2]

While the examples provided represent only a fraction of the growing body of literature on the topic, current empirical research on team-level drivers of innovation is limited in two key ways: First, researchers have predominantly examined the effects of *individual* factors on the innovation outcome, often using methodological approaches that focus on the marginal impacts (e.g., regression models) of these single factors. Consequently, we have limited understanding

[2] The underlying data was obtained from the *PatentsView* database.

of how different factors interact and combine to influence innovation. Second, the effects of team-level factors on innovation outcomes have shown considerable ambiguity across various studies. Scholars attempting to explain these inconsistencies have highlighted the crucial role of the innovation context in shaping the impact of specific team configurations (Joshi & Roh, 2009; Vakili & Kaplan, 2021). Vakili and Kaplan (2021, p. 1161) emphasize that the ambiguity in findings "may be a feature and not a bug", as "insights […] drawn from one domain could potentially lead to undesirable outcomes if applied in another domain with different underlying characteristics". Working in a team of generalists, for example, has been shown to be useful in settings where technological advancements are rather slow, while teams composed of highly specialized members thrive in rapidly changing environments where "their deeper expertise allow[s] them to use new knowledge created at the knowledge frontier" (Teodoridis et al., 2019, p. 894). As a result, despite the progress made, the *causally complex* interactions within team configurations and their influence on innovation outcomes remain largely unexplored in the existing literature. Moreover, given the context-contingency, it becomes essential to specifically examine the clean energy sector with its domain-specific idiosyncrasies to uncover the configurations that lead to success in this unique environment.

1.4 Collaborative Innovation as a Configurational Problem

The question of which team configurations are most effective in driving significant technological advancements is just one example of many phenomena of causally complex nature prevalent in (innovation) management research. Other such inquiries address the interplay of organizational structure, strategy, and the organizational environment in explaining high firm performance (Fiss, 2011); the interaction of formal and informal institutions in determining CEO and employee compensation (Greckhamer, 2016); or how technology traits and research team characteristics impact proof-of-concept (PoC) commercialization outcomes (Battaglia et al., 2021), to name just a few examples. These research problems are generally defined by three main characteristics: *conjunctural causation*, *equifinality*, and *causal asymmetry* (Misangyi et al., 2017). Conjunctural causation occurs when an outcome is influenced by the interdependence of multiple factors rather than a single factor, while equifinality describes the scenario where multiple causal pathways can equally lead to the same outcome. Additionally, causal asymmetry highlights that the presence and absence of factors can have different effects on the outcome, indicating that the factors leading to, for example, success are not simply the reverse of those leading to failure.

Understanding these facets of causal complexity is crucial for grasping why the composition of innovation teams constitutes a causally complex problem: When a team is formed, team-level attributes do not appear in isolation. Instead, any configuration of a team represents a "multidimensional constellation of conceptually distinct characteristics that […] occur together" (Meyer et al., 1993, p. 1175). Teams may be large or small and at the same time to a certain degree demographically diverse, composed of specialists or generalists, with years of innovation experience or no experience at all. Accordingly, a configurational perspective would presume that boundary-shifting developments as an outcome of collaborative innovation would rather relate to certain combinations of these individual attributes (conjunctural causation), instead of any of such factors by itself (Fiss, 2007). Yet, prior research has focused on the relative contributions of individual attributes by predominantly applying bivariate methods that are based on correlations and treat factors as competitors for effects on an outcome. In problems such as the complex interplay of several team-level attributes, however, causal relations are likely not linear. Instead, when the presence of an attribute is commonly associated with better innovation outcomes, it does not necessarily mean that its absence is concurrently associated with particularly bad results (causal asymmetry). Moreover, multiple configurations of team-level conditions may be equifinal, such that they are equally apt to produce high-quality innovation outcomes (Gresov & Drazin, 1997), with some attributes being substitutable (Misangyi & Acharya, 2014) or even irrelevant (Meyer et al., 1993) in some configurations.

While conventional methods, focusing solely on the marginal effects of one or multiple factors on an outcome, may struggle to adequately capture causal complexity, configurational methods explicitly embrace these aspects and provide a toolbox for analyzing the intricate interplay of factors. In the following section, I lay out my specific research objectives for this dissertation, which together seek to outline a path for examining the composition of successful innovation teams through a configurational lens.

1.5 Research Objectives and Dissertation Structure

In light of the identified challenges in understanding team-level drivers of collaborative innovation and the limitations of the current literature, this dissertation presents three main chapters (Chapters 2-4) to chart a path towards a configurational perspective on team-based innovation: Chapter 2 offers a systematic review of the current literature in the field, focusing on the compilation of a comprehensive list of team composition factors and existing insights on their effects on the innovation outcome as a basis for exploring more complex joint effects. I reveal a fragmented research landscape marked by terminological inconsistencies in conceptually similar measures of team composition factors and diverse innovation outcomes. By deriving thematic categories of team composition factors and innovation outcomes, and through reconciling these inconsistencies, I aim to clarify ambiguities in existing empirical findings, thereby synthesizing the relationships that have been empirically examined to date. The wide array of potentially relevant team composition factors identified in the literature review presents a challenge for applying common (set-theoretic) methods to study innovation team composition through a configurational lens. These methods require a carefully curated selection of a limited number of pertinent factors to maintain interpretability of results. Accordingly, Chapter 3 introduces a novel methodological approach for identifying relevant factors in contexts characterized by a multitude of influencing variables, varied empirical support, and limited consensus on key conditions. Finally, in Chapter 4, I present a configurational analysis of teams creating particularly impactful innovations, using data from more than 50,000 granted team-based clean energy patents filed with the *United States Patent and Trademark Office (USPTO)* between 1985 and 2015. This analysis yields insights into specific combinations of team-level conditions associated with innovations that drive technological advancement within the clean energy domain and provides a critical foundation for understanding the complex interplay of factors contributing to successful team-based innovation in that context. Table 1.1 summarizes the research objectives, methodological approaches, data, key findings, and contributions for each of the three main chapters along with an overview of the contributing co-authors and presentations of prior versions of this work to the scientific community.

Table 1.1: Dissertation structure and overview of the three main chapters.

	Chapter 2	**Chapter 3**	**Chapter 4**
Title	**Team Composition and the Effects on Innovation Outcomes: A Systematic Review**	**Patterns that Matter: Clustering-Based Model Specification for Large-N QCA in Complex Theoretical Landscapes**	**A Set-Theoretic Analysis of Innovation Team Configurations**
Research objective(s)	Synthesize and harmonize the landscape of team composition factors and their relationship with innovation outcomes studied in the existing body of research on innovation team composition	Develop and test a data-driven approach to condition selection applicable to large-N set-theoretic analyses in theoretical landscapes characterized by various potential factors and little insight into their relative importance	Identification of team configurations associated with impactful clean energy innovations
Research approach	Systematic literature review, following a multi-stage process similar to Aguinis et al. (2018)	Experimental study using cluster-based model comparison	Large-N set-theoretic analysis (QCA)
Data	808 peer-reviewed journal articles, 54 included in analysis based on article selection criteria	Clean energy patent data	Clean energy patent data

Key findings	- Thematic categories of team composition factors and different types of team-level innovation outcomes
	- Inconsistent use of terminology for conceptually similar measures
	- Sparse landscape of substantive empirical insights on the effects of team composition factors on different innovation outcomes
	- Interaction effects remain underexplored
	- Overrepresentation of regression-based methods
		- A novel clustering-based method for condition selection in large-N QCA reveals a robust set of conditions that demonstrate causal relevance
		- Most relevant set of team composition factors to explain impactful clean energy innovations includes:
		  - Institutional diversity
		  - Ethnic Diversity
		  - Gender Diversity
		  - Knowledge Dissimilarity
		  - Recombination Novelty
		  - Network (Degree) Centrality
		  - Inventor Mobility
			- Multiple, relatively rare and narrow pathways to impactful clean energy innovations exist
			- No single condition (or combinations thereof) is a “must-have”
			- There are no configurations consistently linked to non-impactful innovations
			- Configurations associated with impactful innovations show:
			  - The absence of knowledge dissimilarity emerges as an important condition in most causal pathways

			- Domain experience and familiarity with combining the focal knowledge components (i.e., exploitation rather than exploration) is a key building block - Strong team-internal ties through prior collaborations rather than numerous external ties foster impactful innovations - Teams that have domain experience and experience working together manage to integrate even dissimilar knowledge effectively
Key contribution(s)	- Catalogues team composition factors and innovation outcomes to summarize antecedents of successful team-based innovation - Harmonizes inconsistent terminology into thematic categories to improve comparability and integration of empirical findings and facilitate consistent use of terminology in future research - Synthesizes empirical evidence on relationships between team composition factors and innovation outcomes, highlighting knowledge gaps	- Introduces a systematic, replicable method for condition selection in large-N QCA, addressing challenges arising from theoretical ambiguity and limited case familiarity - Enhances robustness and reliability of QCA analyses in general through a complementary data-driven approach to selecting conditions with genuine causal significance, thereby addressing common criticism about unclear condition selection in QCA studies	- Introduces a configurational perspective on innovation team composition, addressing conjunctural effects, causal asymmetry, and equifinal pathways to impactful innovation
Contributing co-authors	Siddharth Vedula, Claudia Doblinger, Susanne Kurowski	Siddharth Vedula	Siddharth Vedula, Claudia Doblinger
Presentations of previous versions	40th European Group for Organizational Studies (EGOS) Colloquium 2024	40th EGOS Colloquium 2024	DRUID 2022, International QCA Paper Development Workshop (PDW) 2022 & 2023, 40th EGOS Colloquium 2024

2. Team Composition and the Effects on Innovation Outcomes: A Systematic Review

In this chapter, based on a total sample of 808 systematically selected publications, I review 54 articles that empirically investigate the impact of team composition on innovation outcomes. To ensure a structured, transparent, and comprehensive identification of relevant articles (Hiebl, 2021), I built on a multi-stage process suggested by Aguinis et al. (2018). I provide an overview of the various team composition factors and different innovation outcomes studied in the expanding corpus of scholarly work and resolve inconsistencies in terminology used across studies to present a synthesis of existing empirical insights on the topic, thus laying the foundation for a configurational perspective on team-based innovation.

2.1 Aim

Researchers have long been interested in the antecedents of ground-breaking innovations as origins of new technological trajectories (Dosi, 1982). A few decades ago, it was fairly common for the creation and diffusion of significant technological advancements to be attributed to individual star inventors (Narin & Breitzman, 1995; Zucker et al., 2002). However, with a growing stock of knowledge and rising technological complexity, such innovations have increasingly become the product of collaborative efforts by innovation teams – multiple inventors who each bring their own set of skills and perspectives to the table (Jones, 2009; Wuchty et al., 2007). With team-based innovation becoming more prevalent, the research community has paid increasing attention to this trend, resulting in a considerable and growing body of research (Figure 2.1) focused on the composition of innovation teams and its implications for the innovation outcome.

The body of literature that has emerged is composed of a significant number of studies that together examine an extensive list of team composition factors, such as *team size* (e.g., Battaglia et al., 2021; Lee et al., 2015; Wang et al., 2017), the team members' *knowledge bases* (e.g., Cassi & Plunket, 2014; Huo et al., 2019; Vakili & Kaplan, 2021), *experience* (e.g., Beaudry & Schiffauerova, 2011; Jain, 2013; Schillebeeckx et al., 2019), or *demographic* *characteristics* (e.g., Ferrucci & Lissoni, 2019; Kaltenberg et al., 2023; Marino & Quatraro, 2022) and their relationships with various different innovation outcomes. However, developing a deeper understanding of team-based innovation – by applying a configurational perspective to overcome limitations in current research on the antecedents of successful team-based innovation (see section 1.4) – requires a synthesis of empirical findings and insights from this diverse landscape of scholarly work. This review, therefore, seeks to inventory the wide array of team composition factors and innovation outcomes, as well as the relationships between them, that have been investigated over the past decades.

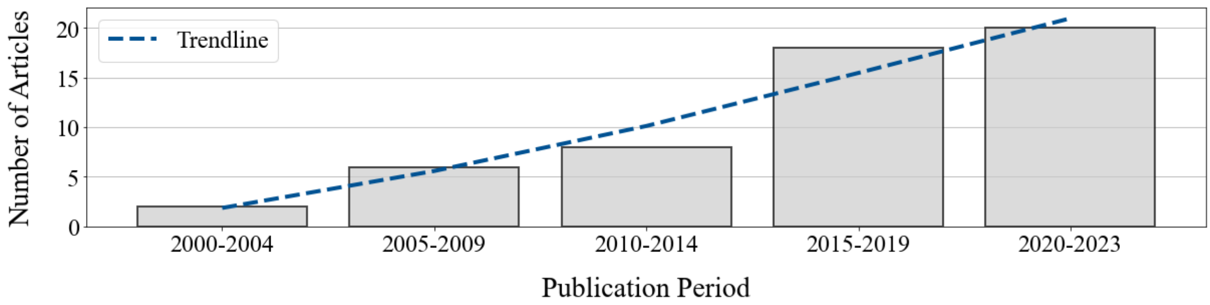


Figure 2.1: Articles on team composition factors and their effects on team-level innovation outcomes by publication period.

Furthermore, in the process of this review, it has become evident that a wide variety of distinct measures as well as the inconsistent use of terminology contribute to a rather unclear picture of the actual factors and relationships examined in the existing literature. For example, while many studies use forward citations of a focal patent to assess the quality of the innovation outcome, the terms used to describe this outcome vary widely. Cassi and Plunket (2014) use the term "inventive performance", Vestal and Mesmer-Magnus (2020) refer to it as "team innovation", and Huo et al. (2019) as well as Onal Vural et al. (2013) use "invention impact" for a conceptually similar, if not identical, outcome. Despite the fundamentally deviating terminology, all these studies examine how that outcome is affected by the similarity of knowledge among team members as a compositional factor, thus investigating essentially the same relationship. Against this background, this review lays a focus on the harmonization of the measures and labels used for similar team composition factors and innovation outcomes to facilitate the integration of knowledge produced across studies and plant the seed for more consistent use of terminology in future research in the field.

2.2 Scope

For this review, I focus on articles from the innovation management literature complemented by articles from a closely related stream of literature on scientific teams. Both literature streams are concerned with technological advancements as the result of research and development efforts by *inventors* or *scientists* and are bibliometrically strongly intertwined. To ascertain a proper level of quality for the research included in this review, I only consider peer-reviewed articles, written in English language, from leading journals in the field. I provide detailed insights into the journal selection procedure (section 2.3) and the article selection procedure (section 2.4) in the following sections. By incorporating articles published in the period from 1997 to 2023, this review covers more than 25 years of research on innovation team composition.

To identify those articles relevant to the aim of this review, I apply a list of diligently defined inclusion and exclusion criteria. Articles were only **included** if they:

i. explicitly examine the relationship between one or more *team composition factors* and one or more *innovation outcomes*.
ii. analyze the relationship defined in (i.) on a *team level*, that is, two or more individuals forming a group to collaboratively innovate (see Katz & Martin, 1997).
iii. explicitly study the team that is *directly performing the innovation*[3].
iv. the study is conducted in the context of *technological innovation*[4].

[3] as opposed to e.g., founding teams or TMTs (e.g., Y. Dai et al., 2019)
[4] as opposed to e.g., service innovation or arts (e.g., Pollok et al., 2021; Taylor & Greve, 2006)

I explicitly **excluded** articles if they:

a. study innovation not on a team level but on a more macro level (e.g., department level, firm level, regional level, etc.).[5]
b. observe outcomes that are not quality-related but process-related (e.g., team coordination, team effort)[6].
c. do not examine compositional but behavioral or psychometric aspects as explanatory factors (e.g., psychological characteristics or personality attributes of the team members)[7].

The application of these inclusion and exclusion criteria was not always obvious. Singh (2008, p. 83), for instance, specifically names the "quality of a *firm's* innovation" as the observed outcome in their study, suggesting that the outcome is measured on a non-team-level. However, the empirical analysis is actually performed on a patent level, hence investigating *team-based* innovation activities and their respective direct team-level outcome (i.e., the patented invention), clearly falling within the scope of this review. On the contrary, other authors use terms like "R&D teams" (e.g., Caputo et al., 2021; Østergaard et al., 2011; Xie et al., 2020) to describe the subject of their study although the analysis is performed on the *department level* of innovating firms. To give a more specific example, Østergaard et al. (2011) and Xie et al. (2020) investigate the effect of gender diversity within "R&D teams" on innovation performance. In these studies, gender diversity is, however, calculated across the entire R&D department of a firm. Yet, drawing on Katz and Martin (1997), I argue that it is crucial to distinguish between team-level analysis and broader scopes like the department or firm level, as "teams are not just scale models of organizations" (Yildiz et al., 2024, p. 1). At these levels of analysis, it is unclear whether innovation outcomes result from the collective efforts of all

[5] e.g., Østergaard et al. (2011)
[6] e.g., Hoegl & Proserpio (2004)
[7] e.g., De Visser et al. (2014)

individuals involved. Typically, R&D departments consist of multiple teams working on different projects. Thus, metrics like gender diversity calculated at the department level may not accurately reflect the diversity among those directly contributing to a particular innovation outcome. Consequently, such “macro-level investigations can offer limited insights” (Yildiz et al., 2024, p. 2) into the team-level antecedents of successful collaborative innovation. Moreover, various studies, such as the one presented in an article by Xie et al. (2020), examine the focal innovation outcome (in that case “innovation efficiency”) at the *firm level*, which makes it even more difficult to trace the impact of the composition of an innovation team to the outcome of a specific innovation project and, thus, of little relevance to the scope of *this review*.

2.3 Journal Selection Procedure

As a foundation for the article selection procedure described in the following section, I first defined an initial pool of sources to consider. This approach aligns with recommended practices outlined by Parmigiani and King (2019), as well as prior reviews by management scholars (e.g., Maula et al., 2023), focusing primarily on the leading peer-reviewed journals within the field of interest. Therefore, in a first step, I selected the top 10% of journals, measured by their *CiteScore*[8], from the 2021 *Scopus* source list in the categories “Management of Technology and Innovation” as well as “Strategy and Management”. I then screened the resulting list of 107 journals to identify those that appear to be central outlets for research that falls within the scope of this review. After thorough appraisal of the scope of each journal, I decided to consider 53 of the initial 107 journals, excluding journals that clearly fall out of the research areas of *Innovation* and *Technology Management* (e.g. *Electronic Commerce Research and Applications, Journal of Family Business Strategy, Journal of Service Management*) as well as method-oriented journals (e.g., *Organizational Research Methods*). However, I tended to be

[8] *CiteScore*™ is a metric developed by *Elsevier* to assess the impact of academic journals based on citation data from the Scopus database (Elsevier, 2024).

rather inclusive when in doubt whether a journal was a relevant source for the scope of this review. In a next step, I followed the same procedure for the *Google Scholar* lists of top publications in the areas "Entrepreneurship and Innovation" and "Strategic Management" as well as for the *Financial Times FT50* list. Each of the two additional Google Scholar lists comprises the top 20 journals in the respective research domain, based on their *h5-indices*[9]. Using complementary journal rankings that apply different measures of source quality and impact allowed me to include 19 additional sources, resulting in a final set of 72 journals in total (Appendix 2.1).

2.4 Article Selection Procedure and Sample Description

To assemble a comprehensive collection of articles pertinent to the scope of this review, I followed a two-stage search strategy, comprising (1) a term-based search within the compiled list of 72 journals selected based on the approach described in the previous section, leading to a core collection of articles included in this review, and (2) a snowball sampling based on references made by the articles in that core collection. In the first stage, the term-based search[10] was conducted by examining the titles, abstracts, and keywords of publications in the *Scopus* and *Web of Science (WoS)* databases. For the Web of Science database, I further used the *KeyWords Plus* feature, which expands the original search term based on "phrases that frequently appear in the titles of an article's references, but do not appear in the title of the article itself" (Clarivate, 2024). This first stage yielded an initial selection of 533 articles. As the primary coder, I then manually evaluated each of these articles based on their title and abstract to classify them as either included or excluded, applying the previously defined criteria (see section 2.2). At this stage, in case of uncertainty, I opted for inclusivity, resulting in a list

[9] The h5-index is the h-index for articles published in the last 5 complete years.
[10] TITLE-ABS-KEY((invent* OR innovat* OR scient* OR research* OR "R&D" OR creative) AND team* AND (config* OR compos* OR characteri*) OR ((invent* AND team*) OR "innovat* team*" OR "scient* team*" OR "research* team*" OR "R&D team*" OR "creative team*")) AND KEY(invent* OR innovat*)

of 112 articles left for more detailed evaluation. It is worth mentioning that, due to the generic nature of the applied search terms (e.g., *team*, *invention*, etc.), I expected to first capture a larger share of non-relevant search results, leading to higher exclusion rates compared to reviews using very specific and subject-related keywords that clearly relate to a narrower stream of literature. In parallel, a subsample of 53 articles (10%) was randomly selected from the initial list of 533 articles and independently evaluated by a secondary coder[11] for validation purposes. For 49 out of these 53 articles (92%), both coders agreed on the inclusion and exclusion, respectively. In all cases of disagreement, the evaluation made by me as the primary coder was more inclusive than the one made by the secondary coder. Accordingly, I proceeded with the 112 pieces selected for an in-depth assessment. After a subsequent review of these articles' full-texts, I identified 41 articles to be of relevance to the defined scope and thus forming the *core collection* of articles included in this review.

In the second stage, I scanned the articles in the core collection for references made to further potentially relevant work. After discarding books, book chapters, and non-peer-reviewed publications, this snowball sampling approach resulted in a list of 251 additional articles that, again, were evaluated based on their title and abstract. Of these 251 articles, 68 appeared to be potentially relevant to this review. Once again, a parallel assessment of a random subsample through the secondary coder was used to validate the article selection decisions made. A disagreement on two articles was resolved through a nuanced discussion between the two coders. Upon conducting full-text reviews of the remaining 68 potentially relevant articles, I ultimately incorporated 13 additional articles, resulting in a comprehensive collection of 54 articles for this review (Appendix 2.2). While four of the articles identified in the second stage were published in journals that were part of the list of journals compiled and employed for the term-based search in the first stage of the article selection procedure, nine of these articles stem

[11] Susanne Kurowski (German Energy Agency - dena)

from eight additional sources (e.g., Nature, Science, Industrial and Corporate Change). The full article selection procedure is illustrated in Figure 2.2. It is worth highlighting that, despite the time period considered in the sampling process – starting in 1997 – there are no articles published before the year 2000 in the final sample, suggesting that the selected timeframe was sufficient to capture the evolution of this literature stream at its inception.

The 54 research papers analyzed in this review are distributed across 24 unique publication outlets, yet certain sources emerge as particularly influential. By far the largest share of articles was published in *Research Policy* (16 publications – 30%), followed by the *Strategic Management Journal* (5 publications), and *Organization Science* (5 publications). Moreover, almost all articles in the sample apply traditional regression-based methods, such as linear regression, negative binomial regression, or logistic regression. Only five papers use different techniques, like more complex multivariate methods (i.e., structural equation modelling), which are applied in three articles, hazard models (1 article), or qualitative comparative analysis (1 article). Furthermore, most studies in the sample draw on patent data, followed by data from scientific publications, and surveys. Table 2.1 offers an overview of the leading research outlets that have been central to the academic discussion on innovation team composition, as well as the most popular methods and data sources utilized.

When scrutinizing the authorship patterns behind the articles, it becomes clear that the literature on innovation team composition is not concentrated around a few leading scholars. Among the 122 unique contributing authors, as few as 13 authors are represented with multiple (co-)authorships. Only one author[12] stands out from that list with four total co-authorships of which three were contributions as the first author. This broad author base highlights the interest in and universal relevance of research on innovation team composition across various institutional settings.

[12] Alex Vestal (UNC Wilmington), OCID: 0000-0002-4514-0002

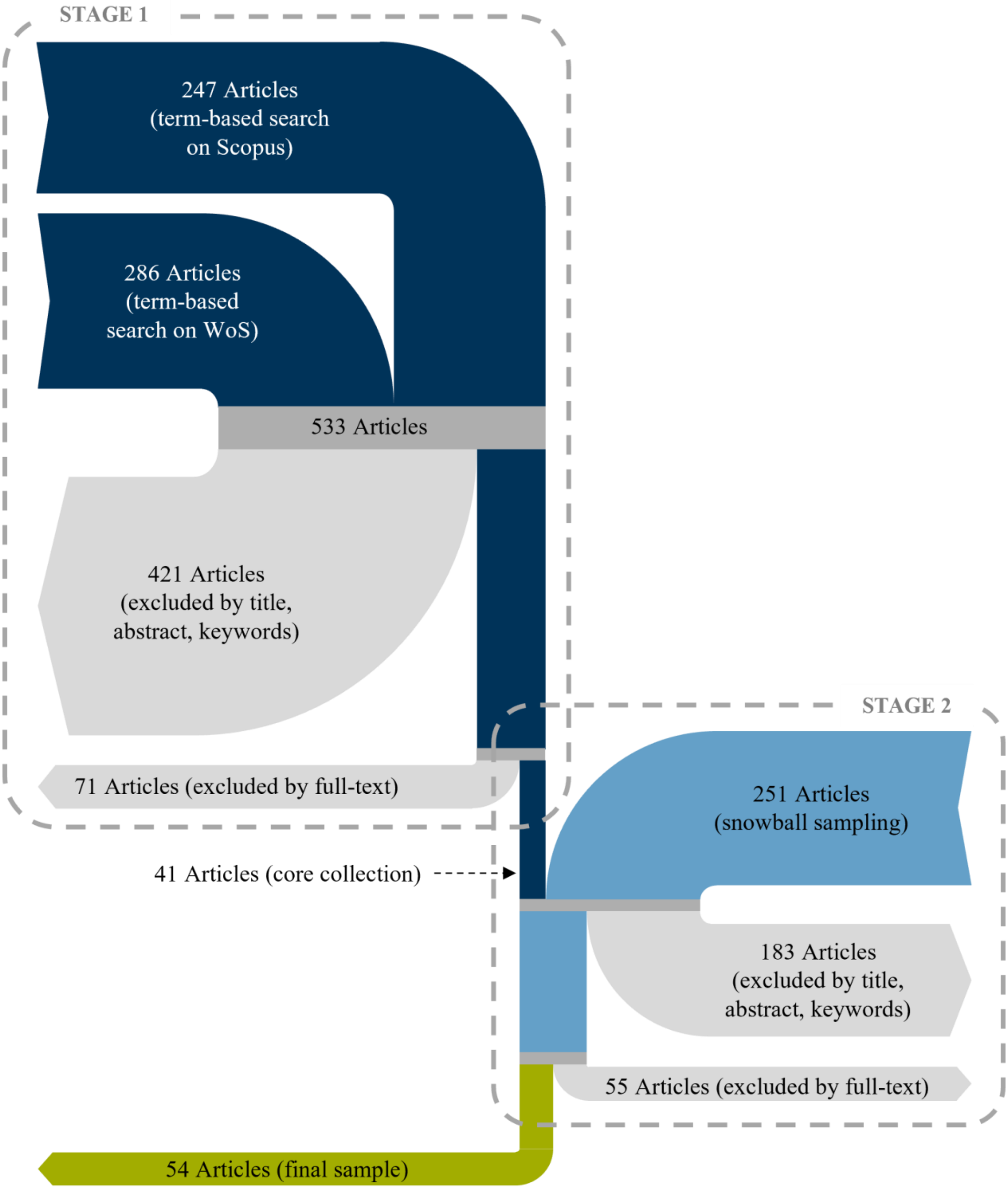


Figure 2.2: Sankey chart illustrating the multi-stage article sampling procedure.

Table 2.1: Breakdown of articles according to journal, methodological approach, and data source.

Source Title	Number of Publications in Sample
Research Policy	16
Organization Science	5
Strategic Management Journal	5
Journal of Business Research	3
Other Journals	25
Method	
Traditional Regression Models	50
Structural Equation Modelling	3
Other Methods	2
Data Source	
Patent Data	35
Scientific Publication Data	8
Survey Data	6
Other Data Sources	12

2.5 Approach to the Analysis

For the analysis of the reviewed articles, I employed a software-aided approach using *MaxQDA*, a tool widely applied by scholars for organizing and analyzing textual research data. During the coding procedure, each article in the collection was thoroughly scanned for (i) team composition factors (independent variables), (ii) innovation outcomes (dependent variables), (iii) moderators, mediators, and contextual factors, (iv) types of data and data sources used, as well as (v) the type of analysis performed (e.g., regression analysis). For the team composition factors, innovation outcomes, mediators, and moderators, I synthesized how each measure was defined and operationalized. Moreover, I collected the empirical findings for the relationships investigated and the theoretical reasoning provided by the authors. Following this coding procedure, I organized the collected factors and outcomes based on the conceptual definition of the measures applied, disregarding the original labels and terminology used by the authors in the focal studies, to address and resolve the issue of *nonmonology* evident in the literature. Through this grouping procedure, I iteratively derived *thematic categories* of different types of team composition factors and innovation outcomes previously investigated in the collection of existing studies. The organized picture resulting from this *harmonization* of the factor and outcome landscapes allows for an easier integration of empirical findings from studies that use different terminology although examining the same or similar relationships.

2.6 Findings

I derived 10 thematic categories of team-level innovation outcomes (Table 2.2) and 17 categories of team composition factors (Table 2.3) that have been explored in the sample of existing work. The analysis of mediating, moderating, and contextual factors yielded few recurring measures, thus not allowing for the development of an informative categorization for these elements. Team composition factors and outcomes each show some categories that have received significantly more attention than others, leading to relatively strong evidence for some relationships and pronounced gaps for others (Table 2.4).

2.6.1 Harmonization of Innovation Outcomes

Studies examining the effects of team composition factors on innovation outcomes encounter two main challenges: the use of generic and inconsistent labels for conceptually similar or even the same measures and the confusion of concepts that are inherently different in their nature. These issues complicate the comparison and integration of empirical findings. Against this background, I first conducted a harmonization – based on the conceptual similarity among the measures employed – for the innovation outcomes studied in the extant body of research, resulting in the identification of 10 thematic categories that encapsulate different types of innovation outcomes. Table 2.2 presents the common measures and original labels associated with each outcome category, along with a concise description of what each category aims to capture. For instance, measures grouped under *commercial utilization* focus on the economic value of an innovation outcome, assessed through metrics such as granted licenses, earned royalties, or the creation of commercial spin-offs.

While certain outcomes have garnered substantial attention from researchers, others appear in only a limited number of studies (Figure 2.3). Additionally, some outcomes, such as *innovation impact*, have been consistently examined over the past two decades, whereas others, like *green innovations*, have only recently emerged as outcomes of interest (Figure 2.4). Early studies have primarily focused on assessing an invention's *superiority* in terms of its innovativeness and overall performance relative to competitors and industry standards, relying on subjective evaluations from experts, consumers, or participants in the innovation process themselves (MacCormack et al., 2001; Sethi, 2000). Over time, patent-based metrics, utilizing, for example, citations or technology classes, have become much more popular across various types of outcomes.

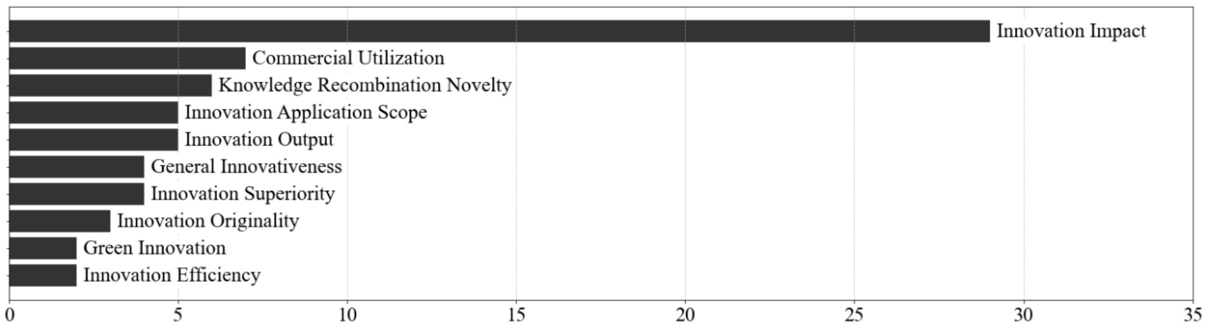


Figure 2.3: Number of articles in sample examining innovation outcomes by thematic categories.

Innovation impact emerges as the most extensively studied outcome, appearing in more than half of the articles analyzed (Figure 2.3). However, it also provides the clearest example of the inconsistency in terminology used across the multitude of studies examining it. For innovation impact, the most dominant measure applied is the count of forward citations received by a patent or research paper that results as a tangible outcome from the innovation project – a common proxy for innovation used in innovation management research (Acs & Audretsch, 1989). The rationale for employing forward citations to assess the impact of an innovation is rooted in the notion that "the very existence of those later patents [or research articles] attests to the fact that the cited patents [or research articles] opened the way to a […] successful line of innovation" (Trajtenberg, 1990, p. 174). Different studies take various approaches to quantify this impact: some use a continuous variable (e.g., Huo et al., 2019; Vestal & Mesmer-Magnus, 2020), while others employ a dummy variable that expresses if the forward citation count of a patent is in a specific quantile compared to other patents filed in the same year and technology class to classify it as a particularly impactful innovation outcome (e.g., Singh & Fleming, 2010; Vakili & Kaplan, 2021). In another indirect citation-based approach, scholars use the impact factor of the publication outlet to evaluate the significance of the innovation (e.g., Franzoni et al., 2018; Yang et al., 2021). Beyond these citation metrics, some authors determine subsequent research as an indicator of lasting impact in a different manner: Battaglia et al. (2021), for example, track whether an initial proof of concept for an innovation led to further research on the technology, and in the context of innovation in the field of molecular life sciences, Zaggl and Pottbäcker (2021) utilize the future number of orders for a newly developed plasmid[13] as the subject of innovation from a gene repository to determine its sustained impact on the research domain.

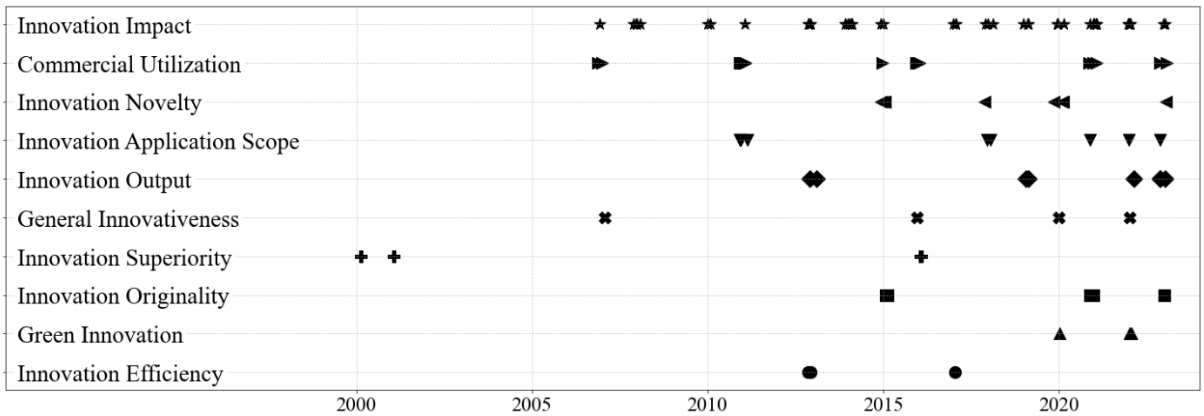


Figure 2.4: Timeline of articles studying innovation outcomes by thematic categories. Note: Each marker represents a single publication. The assignment of publications to thematic categories is not mutually exclusive.

Despite the similarities in underlying ideas and concepts, the diversity in terminology across studies is particularly pronounced in the *innovation impact* theme of outcomes. Although many articles incorporate impact-related terms, an even larger number use labels, such as "economic value" (Chang, 2022), "team performance" (e.g., Ferrucci & Lissoni, 2019), or "breakthrough

[13] A plasmid is a small, circular DNA molecule found in bacteria that exists independently of the chromosomal DNA. Scientists use plasmids in research settings for various applications, especially to introduce new genes into bacteria to add new functionalities. (Pfeifer & Rocha, 2023)

inventions" (Vestal & Danneels, 2022), that mask the fact that the investigated outcomes are fundamentally comparable. Further examples of thematic categories that exhibit notable inconsistencies include *innovation application scope*, *innovation output/productivity*, *innovation superiority*, and *innovation efficiency*. Yet, in these cases, the variety of terms used is somewhat justified by the lower conceptual similarity among the measures employed compared to the *innovation impact* category. In contrast, for *commercial utilization* and *green innovation,* terms applied for the labeling of measures are relatively consistent (Table 2.2).

A second major challenge lies in the confusion surrounding the underlying concepts themselves rather than merely inconsistent terminology. For instance, the line between innovation *novelty* and *originality* is often blurred. These terms are frequently used interchangeably (Kaltenberg et al., 2023; Lee et al., 2015; Vakili & Kaplan, 2021), yet I argue that, conceptually, they are fundamentally different (see also Kelly et al., 2021). Novelty refers to the quality of being new or unusual, which can manifest in two ways: by recombining existing pieces of knowledge in a way that has never been done before, or by introducing entirely new methods or ideas that have no precedent. Novelty can remain merely novel without others building upon it. Originality, on the other hand, should be interpreted in the fundamental sense of the word's root – "origin." It refers to an innovation outcome that serves as the starting point for a new line of innovation or a new technological trajectory (Dosi, 1982). The key distinction lies in the impact of these concepts: while novelty may represent a unique or unprecedented development, originality implies that subsequent work builds upon this originating innovation, driving further advancement.[14] Resolving these ambiguities and clearly defining the specific outcomes examined is essential for making accurate comparisons and integrating insights across studies.

[14] At this point, it is worth mentioning, that innovation *impact* depicts the "counterpart" to innovation *novelty*, with impactful innovations being defined as such that drive further innovation that build on them, without the necessity of being the first of its kind. Hence, innovations of high originality can be seen as such that combine both impact and novelty (see also Kelly et al., 2021).

Table 2.2: Thematic categories of innovation outcomes by conceptually similar measures.

Thematic Category	Measures	Original Labels	Articles
Innovation Impact How an innovation fuels future research and innovation	Patent / paper forward citations	invention impact, innovation impact, patent impact, paper impact, technological impact, research impact	Chang, 2022; Czarnitzki et al., 2011; Freeman & Huang, 2014; Huo et al., 2019; Jiao et al., 2022; Jones et al., 2008; Kerr & Kerr, 2018; Lee et al., 2015; Li et al., 2018; Onal Vural et al., 2013; Schillebeeckx et al., 2019; Seo et al., 2020; Singh & Fleming, 2010; Vestal & Danneels, 2023; Wang et al., 2017; Wuchty et al., 2007
		team performance, innovation performance, inventive performance, team innovation	Cassi & Plunket, 2014; Ferrucci & Lissoni, 2019; Franzoni et al., 2018; Le Gallo & Plunket, 2020; Vestal & Mesmer-Magnus, 2020; Zaggl & Pottbäcker, 2021
		value of invention, value of innovation, economic value, economic breakthrough	Chang, 2022; Li et al., 2018; Singh & Fleming, 2010; Vakili & Kaplan, 2021; Vestal & Danneels, 2022
		breakthrough innovation, breakthrough invention, economic breakthrough	Chang, 2022; Gay et al., 2008; Singh, 2008; Vakili & Kaplan, 2021
		invention quality, patent quality	Czarnitzki et al., 2011; Le Gallo & Plunket, 2020; Wang et al., 2017
		invention importance, patent importance	Czarnitzki et al., 2011; Kaltenberg et al., 2023
	Journal impact factor	team performance, innovation performance, paper impact	Franzoni et al., 2018; Freeman & Huang, 2014; Yang et al., 2021
	Subsequent research projects	new research, team innovation performance	Battaglia et al., 2021; Zaggl & Pottbäcker, 2021
Commercial Utilization How an innovation is turned into economic value	Licenses, royalty dollars	commercialization (success), licensing	Ali & Gittelman, 2016; Battaglia et al., 2021; Bercovitz & Feldman, 2011; Walsh et al., 2016
	Research resulted in (triadic) patents	commercialization (success), economic relevance	Bercovitz & Feldman, 2011; Gittelman, 2007; Melero & Palomeras, 2015
	Spin-off creation	commercialization, spin-off creation	Battaglia et al., 2021; Walsh et al., 2016
	Internal (commercial) use of research	commercialization, proprietary technologies, private value	Gittelman, 2007; Walsh et al., 2016

Innovation Novelty How an innovation combines knowledge in a new way or introduces a new idea without any precedent	Novel combination of patent subclasses	novelty, knowledge recombination, outlier patents	Choudhury & Kim, 2018; Kneeland et al., 2020; Seo et al., 2020; Tzabbar & Vestal, 2015
	Novel combinations of references	novelty	Lee et al., 2015; Seo et al., 2020
	Spread of backward citations across technology classes; number of backward citations	originality, depth of connection to previous technology	Kaltenberg et al., 2023
Innovation Application Scope The breadth of an innovations' potential applications	Number of patent claims	patent (application) scope, invention scope, patent quality	Beaudry & Schiffauerova, 2011; Choudhury & Haas, 2018; Kaltenberg et al., 2023
	Variety of technology classes in forward citations	(technology) generality	Ardito et al., 2021; Kaltenberg et al., 2023
	Spread of patents across technology classes	tech diversity	Chang, 2022
Innovation Output / Productivity The count of successful innovation results (in a certain period of time)	Number of patents / papers produced; likelihood to produce a patent	innovation performance, R&D performance, productivity, rate of patenting	Chang, 2022; Kaltenberg et al., 2023; Yoo et al., 2023
	Time needed to produce a patent	innovative productivity	Jain, 2013
	Completion of a clinical trial	innovation outcome	Brunetta et al., 2019
General Innovativeness Innovativeness measured based on multi-dimensional constructs	Multi-item constructs	team innovativeness, team innovation, innovation performance, knowledge outcome	Cheung et al., 2016; Cummings & Kiesler, 2007; Hubner et al., 2022; Zhang et al., 2020
Innovation Superiority How an innovation performs better compared to other solutions	Expert rating	invention quality, (new) product quality, product performance	MacCormack et al., 2001; Sethi, 2000; Walsh et al., 2016
	Deviation from industry average	R&D team performance	Hoisl et al., 2016
Innovation Originality How an innovation represents the root / origin of a new technological trajectory	Ratio of forward to backward citations	catalyzing effect	Dornbusch & Neuhäusler, 2015
	References similarity between focal patent and forward citing patents	disruptiveness	Kaltenberg et al., 2023
	Topic modelling – textual content novelty	cognitive novelty, novel breakthrough, topic origination	Vakili & Kaplan, 2021
Green Innovation An innovation that reduces environmental degradation	Patent is classified in WIPO IPC Green Inventory or OECD ENV-TECH	green technology	Marino & Quatraro, 2022; Orsatti et al., 2020
Innovation Efficiency The output of innovation relative to the resources required	Number of patent forward citations received per scientist man-days spent	patent quality, patent impact, citations per unit labor requirement	Jain, 2013
	Data Envelope Analysis – multi-item construct	R&D performance	Hung, 2017

2.6.2 Harmonization of Team Composition Factors

Scholars have not only investigated a multitude of different innovation outcomes but have also considered an extensive collection of team composition factors in seeking to explain these outcomes. Employing the same harmonization approach applied to innovation outcomes (section 2.6.1), I derived 17 distinct categorical themes that encompass the range of team composition factors studied in the existing literature (Table 2.3). Many of these categories refer to some sort of diversity, such as *knowledge*, *demographic*, or *functional diversity*, reflecting a shared theoretical assumption that varied perspectives and expertise contribute to innovation. Other categories focus on factors that foster the integration of these perspectives, such as *prior collaboration* and *experience*, supporting the idea of innovation as a process that combines and aligns inputs from diverse sources (Dahlin et al., 2005; Dougherty, 1992; Harvey, 2014; Huo et al., 2019; Schmickl & Kieser, 2008).

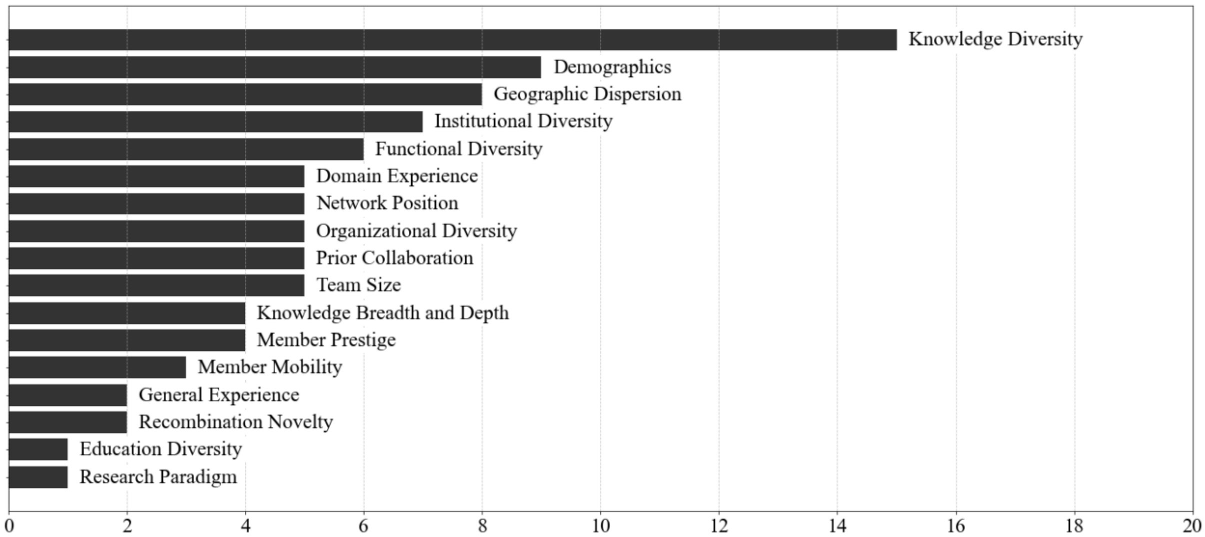


Figure 2.5: Number of articles in sample examining team composition factors by thematic categories.

Knowledge diversity is the most salient team composition factor studied (Figure 2.5). Interest in knowledge diversity emerged relatively recently (Onal Vural et al., 2013) but continued to receive steady attention since (Figure 2.6). With this considerable focus on knowledge diversity has come a high variety in the measures used to assess it. The most common approach relies on historical patent or research publication data to determine each team member's knowledge base, inferred from technology classes (for patents; e.g., Huo et al., 2019; Vestal & Mesmer-Magnus, 2020) or subjects and keywords (for publications; e.g., Onal Vural et al., 2013; Zaggl & Pottbäcker, 2021). Knowledge diversity within teams is typically quantified using vector-based distance measures or categorical diversity indices. Among studies employing these approaches, terminology tends to be consistent and well descriptive, with terms like "technological dissimilarity", "knowledge distance", and "multiplicity in expertise" frequently used. However, some studies adopt alternative labels, such as "collective breadth" (Kneeland et al., 2020). Additional measures for knowledge diversity consider team members' prior experience across various industries (Hoisl et al., 2016), subjects of academic education (Yoo et al., 2023; Zhang et al., 2020), or self-reported expertise (Lee et al., 2015), providing a broader view of the sources of diverse knowledge within teams.

Other diversity factors, such as *demographic diversity* and *geographic dispersion*, have also received significant scholarly attention. Research into demographic aspects – including nationality, ethnicity, age, and gender – only began gaining traction around 2014, reflecting a newer focus on these attributes. Geographic factors, on the other hand, were addressed earlier but have seen a decline in recent years. This trend is even more pronounced for *organizational diversity* (Figure 2.6). Demographic diversity provides a good example of a category of factors with a fair degree of consensus in how measures are applied. For instance, *nationality* is usually operationalized based on citizenship declared at patent filing (e.g., Ferrucci & Lissoni, 2019), while *ethnicity* is commonly estimated by probabilistic methods via surnames (e.g., Marino & Quatraro, 2022). Similar probabilistic methods are used for *gender* and, more recently, *age* attribution (e.g., Kaltenberg et al., 2023), though gender diversity has received surprisingly little attention at the team level[15]. For *geographic dispersion*, direct location data is often used to

[15] A larger collection of studies examines gender diversity at a firm level or department level (e.g., Díaz-García et al., 2013; Garcia Martinez et al., 2016; Østergaard et al., 2011; Xie et al., 2020).

calculate distances between team members or the number of unique locations represented on a team, with a focus either on the benefits of proximity for facilitating knowledge flows (e.g., Seo et al., 2020; Tzabbar & Vestal, 2015) or on the advantages of diverse, spatially bound knowledge in dispersed teams. Studies examining nationality often use similar arguments regarding diverse regional knowledge sources (e.g., Gay et al., 2008). In contrast, a few studies use less direct measures for geographic factors, such as the approach by Beaudry and Schiffauerova (2011) of using foreign patent ownership as a proxy for global dispersion. Here, terminology is clearer when applying distance-based measures (e.g., "geographic proximity") and location-based diversity (e.g., "geographic dispersion") than when using indirect measures (e.g., "global collaborative patent").

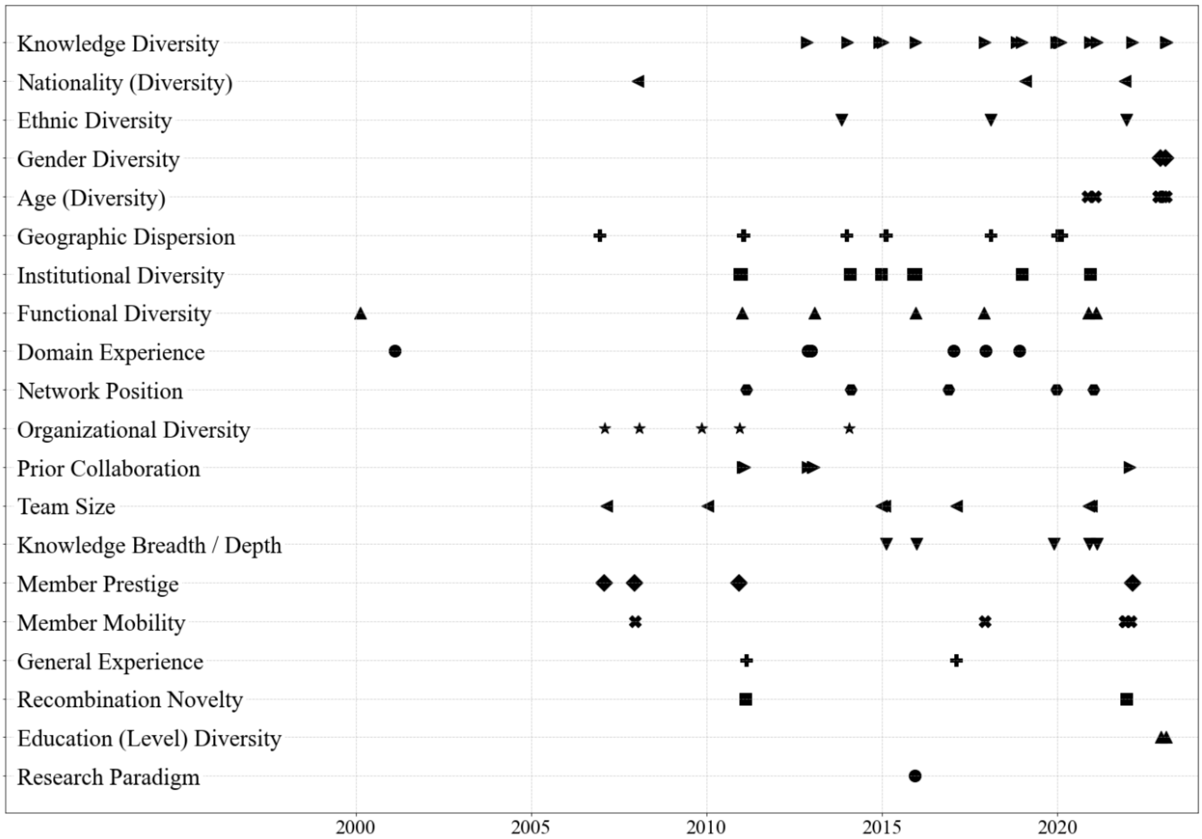


Figure 2.6: Timeline of articles studying team composition factors by thematic categories. Note: Each marker represents a single publication. The assignment of publications to thematic categories is not mutually exclusive. The *Demographics* category is shown disaggregated into its sub-categories: *Nationality*, *Ethnic Diversity*, *Gender Diversity*, and *Age*.

Table 2.3: Thematic categories of team composition factors by conceptually similar measures.

Thematic Category	Measures	Original Labels	Articles
Knowledge Diversity Diversity (variety / dissimilarity) of knowledge / expertise among the members of a team	Diversity / distance measure based on technology classification / subject / keywords of previous publications	technological dissimilarity, technological variety, technological proximity, technological distance, scientific proximity	Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Orsatti et al., 2020; Vestal & Danneels, 2022
		knowledge overlap, knowledge distance, knowledge coherence, cognitive distance	Orsatti et al., 2020; Vakili & Kaplan, 2021; Vestal & Danneels, 2023
		multiplicity in expertise, unsharedness of expertise	Vestal & Mesmer-Magnus, 2020; Zaggl & Pottbäcker, 2021
		collective breadth	Kneeland et al., 2020
		recombinant capabilities	Orsatti et al., 2020
	Self-reported diversity / diversity measure; based on academic education (by subject)	major diversity, knowledge background, explicit knowledge heterogeneity	Yoo et al., 2023; Zhang et al., 2020
	Diversity measure based on experience in different industries	team experience diversity	Hoisl et al., 2016
	Self-reported field expertise	field variety	Lee et al., 2015
	Distance measure based on affiliation with technical communities	informal team diversity	Choudhury & Haas, 2018
Demographics (Diversity of) demographic attributes among team members **Nationality**	Cultural differences linked to countries; separation based on beliefs associated with nationalities	cultural differences, team separation	Ferrucci & Lissoni, 2019; Hubner et al., 2022
	Diversity measure based on nationalities; presence of foreign inventor on team	team diversity, presence of foreign inventor	Ferrucci & Lissoni, 2019; Gay et al., 2008
Ethnic Diversity	Diversity measure based on ethnicities assigned through surnames	ethnic diversity, ethnic homogeneity, inventor ethnicity	Choudhury & Kim, 2018; Freeman & Huang, 2014; Marino & Quatraro, 2022
Age (Diversity)	Team members mean age; standard deviation of age; percentage of members below specific age	team (average) age, age heterogeneity	Battaglia et al., 2021; Kaltenberg et al., 2023
Gender Diversity	Diversity measure based on binary gender	gender diversity	Yoo et al., 2023

Geographic Dispersion The geographic proximity / dispersion of the members of a team	Average pairwise distance between team members locations, average distance of external team members to PI	geographic proximity, geographical distance, team distance	Bercovitz & Feldman, 2011; Cassi & Plunket, 2014; Dornbusch & Neuhäusler, 2015; Gittelman, 2007
	Diversity measure based on number of different team member locations	geographic dispersion, geographic diversity	Seo et al., 2020; Tzabbar & Vestal, 2015
	Team includes member abroad / foreign member	global collaborative patent, involvement of foreign inventors	Beaudry & Schiffauerova, 2011; Kerr & Kerr, 2018
	Patent is assigned to foreign company	foreign patent ownership, foreign collaboration	Beaudry & Schiffauerova, 2011
Institutional Diversity The variety of institutional backgrounds represented on a team (e.g., public / private sector; firm / university)	Categorical variable / dummy measuring diversity of institution types represented on team (e.g., public / private; SME / MNE; firm / university; customer / supplier / competitor); number of different institution types represented on team	team institutional diversity, organizational background, university-industry collaboration, partnership type, collaboration heterogeneity, external network ties	Bercovitz & Feldman, 2011; Brunetta et al., 2019; Dornbusch & Neuhäusler, 2015; Walsh et al., 2016
	Presence of team member with academic background on team	academic patents, presence of scientist	Ardito et al., 2021; Czarnitzki et al., 2011
	Experience in similar institution type	organizational proximity	Cassi & Plunket, 2014
Functional Diversity The variety of job functions represented on a team	Diversity measure based on job function of team members	functional diversity, formal team diversity	Cheung et al., 2016; Choudhury & Haas, 2018; Sethi, 2000
	Diversity measure based on departmental affiliations of team members	team heterogeneity, number of departments, coordination and communication costs	Battaglia et al., 2021; Bercovitz & Feldman, 2011; Onal Vural et al., 2013
Domain Experience Prior experience working / innovating in the focal innovation domain	Similarity of team members' previous patents technology classes with focal patents classes; number of previous patents in same classes as focal patent; share of team members with previous patents in same classes	team domain experience, team specific invention experience, individual experience, exploration	Jain, 2013; Li et al., 2018; Schillebeeckx et al., 2019; Wang et al., 2017
	Number of previous generations of product worked on	generational experience	MacCormack et al., 2001
Team Network Position			
Social Proximity The connectedness of (the members of) a team to non-members	Closeness / degree centrality of team or individual members; based on collaboration and citations of prior work	social proximity, closure, closeness centrality, degree centrality, social network density, technology ties density	Beaudry & Schiffauerova, 2011; Cassi & Plunket, 2014; Hung, 2017; Yang et al., 2021

Gatekeeper Position The degree to which (members of) a team bridge(s) knowledge flows between non-members	Betweenness centrality / structural hole position of team or individual members; based on collaboration and citations of prior work	gatekeepers, gatekeeper functionality, betweenness centrality, structural holes	Beaudry & Schiffauerova, 2011; Hung, 2017; Le Gallo & Plunket, 2020; Yang et al., 2021
Organizational Diversity The diversity of organizational affiliations represented on a team	Number of universities involved	multi-university collaboration	Cummings & Kiesler, 2007; Jones et al., 2008
	Involvement of external organizations; patent assignment to organization	collaborative patent, assigned patent, coordination and communication costs	Bercovitz & Feldman, 2011; Singh & Fleming, 2010
	Prior co-patenting of team members for the same organization	organizational proximity	Cassi & Plunket, 2014
Prior Collaboration The degree to which team members have worked together in the past	Prior pairwise collaborations among team members; prior collaboration of full team; prior collaboration among at least two team members; number of prior collaborations among at least two team members	prior joint work experience, prior ties, preexisting social ties, repeated collaboration, team experience, generalized experience	Beaudry & Schiffauerova, 2011; Bercovitz & Feldman, 2011; Jain, 2013; Jiao et al., 2022; Onal Vural et al., 2013
Team Size The number of team members	Number of members on the team	team size	Battaglia et al., 2021; Lee et al., 2015; Wang et al., 2017
	Dummy if research is performed by more than one person	team	Singh & Fleming, 2010; Wuchty et al., 2007
Knowledge Breadth / Depth The degree of specialization / generalization w.r.t. to the expertise of the team members	Number of team members' previous patents in multiple unique / one single technology class(es); diversity measure based on technology classes of previous patents	knowledge breadth / depth, breadth, presence of generalists	Kneeland et al., 2020; Melero & Palomeras, 2015; Vakili & Kaplan, 2021
	Presence of a team member with multiple distinct degrees	cross-domain inventions	Ali & Gittelman, 2016
Member Prestige The presence of one or more team members with outstanding past performance	Number of a single team member's past patents	star inventors, prolific inventors	Beaudry & Schiffauerova, 2011; Gay et al., 2008
	Member affiliation with highly cited institution	prolific inventors, partner prestige	Gittelman, 2007
	Degree to which cumulative past patents center around one team member	productivity gap	Jiao et al., 2022
Member Mobility How team members have changed locations, organizational affiliations, and partners in the past	Team member(s) changed location in the past	mobile scientist team, cross-regional move	Franzoni et al., 2018; Singh, 2008
	Team member(s) collaborated with someone from another location in the past	cross-regional tie	Singh, 2008

General Experience The overall (domain-independent) innovation experience among the members of a team	Average number of previous patents filed across team members	team general invention experience, average patents per inventor	Beaudry & Schiffauerova, 2011; Wang et al., 2017
Recombinant Novelty How new the combination of knowledge backgrounds introduced by the members of a team is	Novel co-occurrences of technology subclasses; based on team members' previous patents' technology classes	technological recombinant capabilities	Marino & Quatraro, 2022
	Novel combinations of collaborating departments; based on team members departmental affiliations	knowledge combination novelty, cognitive diversity	Bercovitz & Feldman, 2011
Education (Level) Diversity The diversity in education levels among the members of a team	Diversity measure based on education (degree) levels among team members	education diversity, education level	Yoo et al., 2023
Research Paradigm The approach to innovation shaped by the prevailing school of thought among team members (e.g., practitioners vs. theorists)	Type(s) of doctoral degrees among team members	research paradigm, lead inventor degree, single- / cross-domain inventions	Ali & Gittelman, 2016

While some categories, such as the demographic aspects, were straightforward to define in the harmonization process, others required more nuanced considerations. For instance, delineating between *organizational* and *institutional diversity* was challenging due to overlapping labels and theoretical underpinnings. To illustrate, organizational diversity primarily captures the variety of affiliations represented within a team, often measured by the presence of different organizations in a project or by team members' affiliations (e.g., Cassi & Plunket, 2014; Cummings & Kiesler, 2007). In contrast, institutional diversity emphasizes the types of organizations – such as public versus private or academic versus industry (e.g., Brunetta et al., 2019; Cassi & Plunket, 2014) – and the unique operational characteristics that each type brings to the innovation process. Nevertheless, such delineations are still crucial to capture the unique contributions that different factors bring to innovation outcomes. With the resulting harmonized categories of team composition factors in place, combined with the thematic categories of innovation outcomes, a foundation is established to summarize the current state of empirical insights on the specific relationships studied between team composition factors and innovation outcomes.

2.6.3 Relationship Synthesis

Inconsistencies in terminology and variations in definitions of measures created significant barriers to the comparison and synthesis of empirical insights across studies, resulting in a fragmented understanding of how team composition impacts innovation outcomes. After disentangling the landscape of team composition factors and different types of outcomes examined in the existing literature, and as a result of systematically cataloging the empirical evidence from this diverse body of research, Table 2.4 presents a cohesive overview of the findings from past studies on team-based innovation.

Following an approach similar to Perkmann et al. (2021), I assigned directional indicators to capture the overall effect of each team composition factor on different innovation outcomes across studies. A (+) marker indicates that studies consistently find a positive relationship between a team composition factor and innovation, even if some studies report non-significant results. A (-) marker signifies that studies consistently report a negative relationship, again, allowing for non-significant findings alongside. The (∩) marker is used when studies identify a curvilinear (e.g., inverted U-shaped) relationship, allowing for both linear (positive or negative) and non-significant results in certain cases. Finally, I assigned an (O) marker where studies show either no significant effect, mixed or contradictory effects, or effects that vary depending on moderators or contextual factors, reflecting ambiguity in the relationship. For each cell in the table, the strength of the fill color indicates the number of studies investigating the specific relationship, providing a visual cue on the volume of evidence available. Additionally, the number of studies is shown in brackets following the relationship marker, making it easy to interpret both the direction and the quantity of research on each relationship (i.e., robustness of the evidence base).

As evident from Table 2.4, the most salient relationship studied is between *knowledge diversity* – and *dissimilarity*[16] among team members' knowledge bases in particular – and the *impact* of an innovation. This is not surprising as both stand out as the most studied categories among team composition factors and innovation outcomes. Studies consistently report a net positive effect that indicates that as knowledge dissimilarity increases, it generally benefits the impact of an innovation as it enables the novel combination of distinct, often complementary knowledge bases, leading to solutions that stand out in the field and thus serve as building blocks that other inventors find particularly valuable for subsequent innovations (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022, 2023; Vestal & Mesmer-Magnus, 2020). However, as knowledge dissimilarity continues to rise, the benefits

[16] Diversity can be disaggregated into different types: separation, variety, and disparity (Harrison & Klein, 2007). *(Knowledge) dissimilarity* refers to the separation aspect of diversity and is conceptually different from *knowledge variety*.

begin to taper off, and a negative quadratic effect (i.e., inverted U-shape) dominates (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020). At such a high level of dissimilarity, it becomes increasingly challenging for inventors to integrate knowledge and perspectives effectively. Coordination costs become higher as team members face significant communication barriers and require additional time and efforts to bridge conceptual gaps. This makes it harder to synthesize the distant knowledge pieces into a cohesive innovation, reducing the overall impact (see also Dougherty, 1992; Harvey, 2014). Interestingly, Huo et al. (2019) find that the overall positive effect of knowledge dissimilarity becomes insignificant when accounting for the *variety* of knowledge held among the inventors, suggesting that – while dissimilarity in knowledge does not necessarily have to come with large knowledge variety (e.g., when highly specialized inventors from different narrow fields collaborate) – the main benefit comes from drawing on a broad knowledge base formed by the collaborating inventors collectively (Vestal & Danneels, 2023; Zaggl & Pottbäcker, 2021).

A similar pattern emerges for other diversity-related aspects of team composition. For instance, Kerr and Kerr (2018) demonstrate that patents filed by inventors across multiple countries tend to yield more impactful innovations, as locally distinct perspectives and specialized knowledge expand the pool of resources available to the team. However, as Seo et al. (2020) show, when *geographic diversity* becomes too high, the benefits are outweighed by coordination and integration challenges, including limited face-to-face interaction and cultural differences, which complicate collaboration.

Yet, other team composition factors specifically foster the integration of diverse perspectives. Profound *domain experience*, for example, helps teams to more effectively select and recombine relevant distinct knowledge pieces through their deep understanding of the field (Li et al., 2018; Schillebeeckx et al., 2019; Wang et al., 2017). At the same time, extensive domain experience can cause cognitive rigidity, making teams depend heavily on familiar approaches and find it challenging to incorporate highly novel components (Wang et al., 2017). In addition to specific experience in the focal domain, Wang et al. (2017) find a similar effect for general, domain-independent experience that inventors gain from previous innovation projects. This *general experience* allows inventors to develop routines that enhance communication and facilitate knowledge integration. However, as with domain-specific experience, extensive general innovation experience can lead to over-reliance on familiar approaches, limiting exploration and reducing the potential for highly impactful innovations.

While the empirical findings for the relationships discussed above are relatively consistent, there remains ambiguity in others. For instance, Lee et al. (2015) find that as *team size* increases, innovations tend to become more impactful, primarily because larger teams access broader networks, enhancing their visibility in the scientific community and increasing the likelihood that other inventors will build on their work. Conversely, Wang et al. (2017) observe diminishing returns with very large teams, where coordination challenges start to offset the benefits of additional members. Battaglia et al. (2021) add nuance by finding that team size is not always a decisive factor. However, when it is relevant, smaller teams are often more effective in producing impactful innovations that stimulate further research.

For certain innovation outcomes, such as *innovation impact*, a stronger empirical foundation exists regarding their antecedents, partly due to the substantial attention these outcomes have received compared to others. In contrast, for *green innovation*, although attracting growing interest in the scholarly community in recent years (Takalo et al., 2021), only a fraction of potentially relevant team-level drivers has been studied. The same is true for *original* (i.e., topic-originating) innovations that constitute the starting point for completely new technological trajectories. Additionally, the informative value of empirical findings varies notably across outcome categories, with some showing more conclusive evidence than others. While prior research shows relatively consistent and significant effects for outcomes like *innovation novelty*, *application scope*, and *efficiency*, the antecedents of innovations with high *commercial utilization* remain relatively ambiguous and less well understood.

A similar imbalance in empirical evidence exists among the team composition factors examined in prior research. While knowledge-related antecedents of successful team-based innovation have been explored across a wide range of outcomes, others factors, such as differences in *education levels*, the inventors' roles as practitioners or theorists (i.e., *research paradigm*), or demographic aspects like *gender diversity* – which has been studied much more commonly on a firm or department level (e.g., Díaz-García et al., 2013; Garcia Martinez et al., 2016; Østergaard et al., 2011; Xie et al., 2020) – remain less examined for many key innovation outcomes. Interestingly, *team size* – a factor extensively studied in relation to *innovation impact* – has been largely overlooked for other frequently examined outcomes, such as *team productivity* or the *application scope* of an innovation.

Furthermore, some team composition factors demonstrate relatively consistent effects across different innovation outcomes. For instance, *ethnic diversity* tends to have positive effects, although these may diminish at very high diversity levels. Similarly, teams with prior *experience in the focal domain* often show enhanced performance across outcomes. In contrast, teams with a higher *average age* tend to produce more *novel innovations*, yet these often have a narrower *application scope* and a lower likelihood of initiating a new technological trajectory that others will build upon (i.e., limited *innovation originality*). Additionally, collaborations between inventors from *different types of institutions* generally result in more *impactful*, *original*, and competitively *superior innovations*. However, *institutional diversity* can reduce a team's *productivity*, as such teams tend to produce fewer innovations over time. Notably, the number of organizations involved in an innovation project (i.e., *organizational diversity*) appears to negatively affect multiple outcomes, with innovations from these teams often being less *economically valuable* and *generally less innovative*.

Table 2.4: Relationship synthesis.

		Innovation Impact	Commercial Utilization	Innovation Novelty	Innovation Application Scope	Innovation Output / Productivity	General Innovativeness	Innovation Superiority	Innovation Originality	Green Innovation	Innovation Efficiency
Knowledge Diversity	Dissimilarity	∩ (6)			+ (1)	O (1)			O (1)	O (1)	
	Variety	+ (3)		+ (2)		∩ (2)	O (1)	∩ (1)		O (1)	
Demographics	Nationality (Diversity)	O (2)					O (1)				
	Ethnic Diversity	+ (1)		+ (1)						∩ (1)	
	Gender Diversity		O (1)			∩ (1)					
	(Average) Age		O (1)	+ (1)	- (1)				- (1)		
	Age Diversity			O (1)	+ (1)				- (1)		
Geographic Dispersion		∩ (4)	O (2)	∩ (2)	+ (1)				O (1)		
Institutional Diversity		O (2)	O (2)		O (1)	- (1)		+ (1)	+ (1)		
Functional Diversity		O (2)	O (2)		+ (1)		- (1)	O (1)			
Domain Experience		∩ (3)				+ (1)		+ (1)			+ (1)
Network Position	Social Proximity (Degr. Centrality)	+ (3)			+ (1)						+ (1)
	Gatekeeper (Betw. Centrality)	+ (2)			+ (1)						+ (1)
Organizational Diversity		O (3)	- (1)				- (1)				
Prior Collaboration		O (2)	+ (1)		- (1)	+ (1)					+ (1)
Team Size		O (5)	O (1)	∩ (1)							
Knowledge Breadth / Depth	Breadth (Generalists)	O (1)	O (2)	+ (1)					O (1)		
	Depth (Specialists)	O (1)							O (1)		
Member Prestige		+ (2)	- (1)		+ (1)						
Member Mobility		+ (1)			+ (1)	O (1)					
General Experience		∩ (1)			O (1)						
Recombination Novelty			+ (1)							+ (1)	
Education (Level) Diversity			O (1)			+ (1)					
Research Paradigm (Practitioners vs. Theorists)			+ (1)								

Notes: The table reports the synthesized qualitative effects of team composition factors on innovation outcomes. (+) positive effect, (-) negative effect, (∩) curvilinear relationship, (O) ambiguous or only non-significant findings.

In summary, while a substantial body of research has investigated relationships between various team composition factors and innovation outcomes, notable gaps and ambiguities remain. Table 2.4 provides an overview of these relationships, highlighting the robustness and directionality of empirical findings across studies. However, the synthesis also reveals that many potential relationships have either limited or inconclusive evidence, creating a fragmented understanding of how different aspects of team composition influence specific innovation outcomes.

2.6.4 Mediators, Moderators and Contextual Factors

Despite the extensive research on team composition and its effects on innovation outcomes, limited attention has been given to interaction effects – particularly the roles of mediators, moderators, and contextual factors that shape these relationships. This focus on direct relationships overlooks the complex dynamics behind these associations.

Mediating factors, for example, serve as explanatory links that help better understand the underlying mechanisms that determine how and why observed relationships take shape, thus offering insights that direct relationships alone cannot fully capture. Vakili and Kaplan (2021, p. 1174) highlight this by showing that an innovation's impact is largely determined by its *originality*, noting that "very little else in team configuration matters for creating […] breakthroughs beyond the indirect effects mediated through producing topic-originating patents". Similarly, Singh and Fleming (2010) find that the advantage teams have in producing more impactful and fewer low-quality innovations stems from the *broader networks* and more *diverse knowledge* bases contributed by multiple inventors. Lee et al. (2015) support this by suggesting that the effect of team size on innovation novelty may arise primarily from the greater *functional* and *knowledge diversity* that larger teams can harness. However, as Cheung et al. (2016) point out, functional diversity can also inhibit *knowledge sharing* across team members which can be detrimental to the innovation success of a team – an effect that is also observed when innovation projects span several organizational boundaries and a great division of central responsibilities among team members results in *poor project coordination* (Cummings & Kiesler, 2007). Finally, Hubner et al. (2022) find that it is the inclination of inventors stemming from certain cultural settings to engage more in *exploration* over exploitation activities that primarily determines innovativeness rather than other cultural idiosyncrasies. When aiming for high impact, however, Wang et al. (2017) demonstrate that teams with some, but not extensive innovation experience are those that create innovations that drive further research most by *balancing exploration with exploitation* of existing knowledge.

Moderators, on the other hand, specify conditions that influence the strength or direction of relationships. The line between moderators and contextual factors is often blurred, as certain conditions can simultaneously influence specific interactions and define the overarching setting under which (interaction-)effects take place. For instance, Orsatti et al. (2020) find that the likelihood of teams with diverse knowledge bases producing green innovations is higher for *less experienced* teams, whereas for *highly experienced* teams, this relationship between knowledge diversity and green innovation even turns negative – demonstrating that team-level innovation experience operates as a clear moderator. Yet, the contrary effects for experienced and unexperienced team becomes even stronger when the country in which an innovation is developed has low environmental *policy stringency*. Here, policy stringency could be seen as a deeper-level moderator, as it systematically affects the strength of the team experience effect on innovation. Alternatively, it may serve as a contextual factor, creating an overarching environmental setting that amplifies or attenuates interactions between team experience and innovation outcomes. Adding to this complexity, *specificities of the sector* as the innovation context further shape the conditions under which green innovations are most likely to emerge, underscoring the challenges in clearly distinguishing moderators from contextual factors. Despite these considerations, however, the set of contextual factors that can be synthesized remains relatively sparse.

While moderating factors appear to be more commonly studied than mediators in the existing literature, each moderator is typically investigated in only a few studies – or even a single study – within the context of a specific primary relationship. Such factors include the *geographic* (Ardito et al., 2021; Cassi & Plunket, 2014; Le Gallo & Plunket, 2020) and *social* (Cassi & Plunket, 2014) *proximity* of team members, *prior experience* and *differences in experience* innovating among team members (Orsatti et al., 2020; Seo et al., 2020; Vestal & Mesmer-Magnus, 2020), a team's *network position* (Schillebeeckx et al., 2019; Yang et al., 2021), and the *diversity of institutional settings* in which team members have previously innovated (Cassi & Plunket, 2014; Dornbusch & Neuhäusler, 2015; Le Gallo & Plunket, 2020), to name a few. One exception stands out: *prior collaboration*, which has been explored as an influential factor across multiple primary relationships. For example, Onal Vural et al. (2013) examine the effects of prior collaboration among team members on the relationship between functional diversity and innovation impact, demonstrating that prior collaborations can transform the otherwise negative effect of high functional diversity within a team into a positive one. Prior collaboration has also been shown to enhance the positive effect of experience in a focal domain on team productivity (Jain, 2013), amplify the impact of exploration-driven innovation (Li et al., 2018), and support the recombination of distant knowledge (Vestal & Danneels, 2023). However, prior collaboration can constrain the innovation scope. For example, Ardito et al. (2021) find that prior collaboration within teams comprising both academic and non-academic inventors may lead to a narrower problem focus, making university-industry teams more likely to concentrate on a more specific issue with repeated collaboration.

Existing research has expanded our understanding of how team composition impacts innovation outcomes. Yet, the exploration of mediators, moderators, and contextual factors remains limited and fragmented. Mediators provide essential insights into the mechanisms underlying direct relationships, while moderators and contextual factors reveal the conditions under which these relationships may change. However, the scarcity of studies investigating these effects leaves significant gaps in the literature. Addressing these gaps is crucial to develop a more nuanced understanding of the complex dynamics associated with team-based innovation.

2.7 Discussion

Over the past 25 years, scholars have shown significant interest in team composition factors that drive successful collaborative innovation. A wide array of factors and innovation outcomes have been examined, making it challenging to maintain a comprehensive overview of the team-level drivers identified in the ever-growing body of scholarly work. This review takes stock and maps out the landscape of team composition factors and innovation outcomes, as well es the relationships between them, addressed in past studies.

During the process of conducting this review, considerable inconsistencies in the terminology used to describe conceptually similar or identical measures became evident, complicating the understanding of which factors and relationships are being studied. To address this issue, I derived thematic categories beyond the authors' original labels and descriptive terms – 10 categories for innovation outcomes and 17 categories for team composition factors – based on the conceptual similarity of the measures employed. These clearly labeled themes reflect what the measures are "actually" assessing, promoting more consistent terminology in future research.

Furthermore, this review shows how certain thematic categories have received significantly more attention than others, with some enjoying continuous scholarly interest over many years, whereas others (e.g., *green innovation*) have only recently gained popularity. While some relationships between team composition factors and innovation outcomes are well-researched (e.g., *knowledge diversity* → *innovation impact*), the majority of potential relationships remain understudied or unexplored. Moreover, although studies show that the innovation context can have a substantial impact on the antecedents of successful team-based innovation (Vakili & Kaplan, 2021), contextual factors and moderators, that can influence the direct effects between team composition factors and innovation outcomes, are featured in only a small fraction of previous studies.

2.7.1 Contributions

With this review, I contribute to research on innovation team composition in three key ways. First, I offer a catalogue of team composition factors and different innovation outcomes discussed in the growing body of literature on the topic, thus providing a comprehensive summary of the factors that have been considered as antecedents of successful team-based innovation. Second, by addressing the inconsistencies in terminology used to describe various measures and organizing them into thematic categories with less ambiguous labels, this review helps to facilitate the comparability of empirical findings and to integrate insights across studies while encouraging more consistent use of terminology in future research. Without consistent terminology, researchers risk various issues, such as conflating different types of outcomes, which can lead to ambiguous results and hinder the development of a coherent body of knowledge. Hence the harmonized categories of team composition factors and different types of outcomes can serve as a framework for future research in the field. Third, by synthesizing the empirical evidence for relationships between team composition factors and innovation outcomes, I provide an overview of the current knowledge on the contribution of team composition factors for fostering specific outcomes and identify a notable range of gaps in the literature as many relationships remain understudied. With that, I provide a roadmap for future research that is crucial for advancing our understanding of how various factors influence innovation outcomes, thereby guiding scholars towards unexplored areas that hold potential for significant contributions.

2.7.2 Limitations

Despite the contributions of this review, there are limitations that need to be acknowledged. First, the scope of this review is limited by design with inclusion criteria being strictly focused on studies that specifically investigate innovation on a team level and in a technological context. For this review, I excluded a notable number of studies that indeed name "R&D teams" as their subject of analysis, but in fact do not comply with the clearly delineated definition of a team (i.e., two or more individuals forming a group to collaboratively innovate) I apply. Instead, these studies often look at entire R&D departments or even the firm level in their analysis. The exclusion of these articles is based on the premise that team composition factors and outcomes observed at these more macro levels do not reliably reflect the collaborative efforts of individual teams, which is crucial to understand the team-level dynamics in collaborative innovation. Nevertheless, despite not meeting the sampling criteria for this review, they could potentially offer insights transferable to the team level as well. Moreover, while this review concentrates on technological innovation, it is important to acknowledge that studies in the context of other types of innovations, such as service innovations or artistic creative work (e.g., Pollok et al., 2021; Taylor & Greve, 2006), despite very different underlying characteristics (e.g., degree of complexity), could still offer additional insights. Furthermore, by focusing exclusively on English articles published predominantly in journals from the field of (innovation) management, this review may have overlooked valuable contributions available in other languages or from other adjacent disciplines. Finally, this review provides a qualitative overview of team composition factors, innovation outcomes, and the relationships between them. Future research could benefit from conducting a meta-analysis to quantitatively integrate findings on effect sizes to further enhance our understanding of these dynamics.

2.7.3 Future Research

Despite the extensive array of team composition factors studied, certain elements remain underrepresented in the literature. To develop a deeper understanding of the antecedents of successful team-based innovation, the scholarly community should aim to close these evident gaps rather than continually focusing on factors for which a solid theoretical and empirical foundation already exists. In particular, innovation outcomes that are crucial for addressing the grand technological challenges of our time – such as *green innovation* – call for increased attention in future research. Furthermore, it is essential to delve deeper into the underlying mechanisms of the relationships between team composition factors and the innovation outcome. This requires moving beyond a sole focus on direct effects to also consider mediating factors that can elucidate how and why certain team compositions lead to specific innovation outcomes. Additionally, investigating the conditions under which these relationships hold true is critical. This involves considering interaction effects, such as moderators and contextual factors, which can significantly influence the strength and direction of the observed relationships.

Methodologically, there is a need to diversify beyond the prevalent use of traditional regression-based methods. Employing alternative approaches, such as configurational methods, could provide richer insights into the complex interplay of multiple team composition factors and their cumulative impact on innovation outcomes. Such methodological diversity can help capture nuances that are often overlooked in regression-based analysis alone.

Finally, I encourage the publication of studies with null or negative findings to provide a more balanced and comprehensive view of the field. The tendency to report only significant positive results can lead to a publication bias, which skews our understanding of the true nature of the relationships between team composition and innovation outcomes. This way, the academic community can foster a more accurate understanding of what drives successful team-based innovation.

3. Patterns that Matter: Clustering-Based Model Specification for Large-N QCA in Complex Theoretical Landscapes

This chapter introduces a novel data-driven approach to the selection of relevant conditions for a set-theoretic analysis. This approach aims to facilitate a meaningful selection of conditions when traditional theory-driven selection is challenging due to a lack of a substantive theoretical foundation. Using a clustering-based approach, and by leveraging data from a comprehensive dataset of clean energy patents, this chapter identifies a set of team composition factors that demonstrate genuine causal significance based on robust co-occurrence in set-analytic models that best explain impactful innovations and thus lays the foundation for a subsequent in-depth configurational analysis.

3.1 Qualitative Comparative Analysis (QCA) and the Trend to Large-N Studies

Qualitative Comparative Analysis (QCA) (Ragin, 2000, 2008) is a set-theoretic method that has been applied widely in management research to address causally complex problems from a configurational perspective (Misangyi et al., 2017). QCA uses *cases* that each exhibit certain attributes (*conditions*) that are theoretically relevant to explain an observed *outcome*. The notion behind QCA is that the degree to which any of these attributes are present in each case can be expressed as a *set membership* (Fiss, 2007). As a result, a truth table is generated, linking each case to a specific configuration – a unique logical combination – of set memberships for all conditions and the outcome. Multiple cases may correspond to the same configuration, indicating they share very similar characteristics and exhibit comparable degrees of set membership. In a subsequent step, the truth table is minimized using the *Quine-McCluskey* algorithm based on Boolean algebra to identify configurations that are consistently associated with the observed outcome.[17]

QCA was originally developed for small numbers of cases (approx. 10-50 cases) for which the researchers hold in-depth case knowledge. However, in recent years, there has been

[17] A more detailed introduction to set-theoretic methods and QCA is provided in Chapter 4.

a trend in the scholarly community around the application of QCA towards more large-N (approx. 50-100 cases) or even very large-N (hundreds or thousands of cases) studies. While there is an ongoing discussion on whether such studies still sufficiently acknowledge the qualitative nature of QCA in its original form, the set-theoretic approach behind QCA has proven valuable for a more quantitative analysis of larger samples as well (e.g., Greckhamer et al., 2008; Leppänen et al., 2023; Miric & Fiss, under review). Yet, the growing number of large-N studies has also been accompanied by new challenges that arise from the loss of connection to the cases. For example, in defining the thresholds that determine the set membership of cases (*calibration*) for the conditions and the outcome of interest, anchors that separate members from non-members of a set need to be chosen. Finding these anchors is of high relevance as it has a direct impact on the results of the analysis. However, that calibration process is not always trivial. Traditionally, QCA scholars turn to the cases in their small-N samples to find meaningful thresholds that, for instance, separate a small from a large team. This becomes more challenging for larger numbers of cases as the distance between the researchers and the cases studied becomes relatively larger as well (Greckhamer et al., 2013; Rutten, 2022). Similar challenges arise for model specification in large-N QCA. In the following section, I elaborate on how relevant input conditions are usually selected and address circumstances under which the lack of case knowledge can lead to additional challenges in the process of specifying a model for large-N studies.

3.2 Selecting Conditions in QCA

As in any non-configurational, net-effects-based regression model, model specification plays an important role in QCA and can significantly affect the results of an analysis. Hence, every QCA model needs to include those causal conditions that are *relevant and central* to – in conjunction – explain the outcome of interest. Although the mechanics behind QCA technically allow for large numbers of input conditions, there are two central limiting factors: First, as the number of possible configurations grows exponentially with the number of input conditions, the likelihood of configurations with no empirical instances increases for a fixed number of cases. This effect of “limited diversity” can – when severe – lead to an undesirable scenario of “individualizing explanations of each particular case; this means that [QCA] will have missed its purpose of reaching some degree of parsimony” (Rihoux & De Meur, 2009, p. 48). While this problem is naturally more pronounced in small-N settings (Marx, 2010), the second limitation applies independently from the number of cases studied: As the model becomes more complex (i.e., a larger number of conditions), the findings become significantly more difficult to interpret (Greckhamer et al., 2018; Greckhamer et al., 2013). Previous studies have pointed to a limit of approximately *six to seven* conditions (Greckhamer et al., 2018; Greckhamer et al., 2013; Marx, 2010) that can reasonably be included in a model to maintain interpretability of the results.

In many applications of QCA, the number of potentially relevant conditions exceeds what can be feasibly included in the analysis. To build a meaningful model, QCA scholars traditionally draw on two main sources of knowledge. First, as the “selection of the characteristics deemed important should be based on theoretical and substantive knowledge about their relationship with the outcome” (Fiss, 2007, p. 1184), researchers turn to the literature to make theory-informed decisions. Second, researchers have the option to turn to the cases and use their in-depth case knowledge. As discussed in the previous section, the latter approach becomes much more difficult to accomplish for large-N settings in which the connection to the cases will naturally fade. Moreover, QCA scholars are commonly facing a theoretical landscape that has mainly been following a net-effects based rational and “for many outcomes configurational theories may not be readily available” (Greckhamer et al., 2018, p. 487). While knowledge on isolated effects can still provide some guidance for the selection of relevant conditions, this approach will only yield a meaningful model if the research field has established a clear theoretical foundation. This, however, is often not the case. Hence, I argue that configurational analyses that (1) are conducted in a large-N setting with a naturally larger distance from the cases and (2) face a complex and ambiguous theoretical landscape characterized by numerous influencing factors, varying empirical support, and limited consensus on key conditions, call for an alternative approach to the selection of relevant conditions.

3.3 A Data-Driven Approach to Selecting Conditions

To effectively navigate the outlined challenges, I propose a *data-driven* approach to selecting the most relevant conditions that seeks to find robust patterns in combinations of conditions that best explain the outcome of interest. By comparing all potential models (i.e., combinations of potentially relevant conditions) based on each model's solution consistency (i.e., "the degree to which the cases [explained by the model][…] agree in displaying the outcome in question"; Ragin, 2008, p. 44) and coverage (i.e., "the degree to which [the model] accounts for instances of an outcome"; Ragin, 2008, p. 44), I identify the best-performing models for various numbers of conditions considered. I then use a clustering algorithm to find those combinations of conditions that commonly co-occur among these best-performing models.

It is a well-established practice for QCA scholars to turn to the data itself when theory is lacking. For example, scholars have used *natural breakpoints* in the data or percentiles of data distributions to make a choice for calibration thresholds when external standards are not available (e.g., Greckhamer, 2016; Gupta et al., 2020; Leppänen et al., 2023). Moreover, in recent years, several proposed methodological enhancements have complemented QCA with other methods to leverage and combine their individual strengths (e.g., Haynes, 2014; Meuer & Rupietta, 2017; Rupietta & Meuer, 2024). For example, Haynes (2014) runs a cluster analysis preceding the QCA for initial data exploration before the QCA is then used to gain an in-depth theoretical understanding of the emerging clusters; Meuer and Rupietta (2017) integrate QCA with hierarchical linear modeling and thus introduce a mixed-method approach that facilitates "multilevel research on organizational configurations" (Meuer & Rupietta, 2017, p. 338); and Rupietta and Meuer (2024) combine QCA with sequential process analysis to capture temporal aspects in configurational phenomena. QCA has also been combined with statistical methods specifically in the context of condition selection. For instance, Meuer et al. (2015) use a principal factor analysis to ensure that the conditions selected for a QCA are statistically relevant and accurately reflect the underlying dimensions of the explained outcome. With the approach I describe in the following sections, I present a tool that can guide the selection of conditions when the number of potentially relevant factors is high, in-depth case knowledge is limited, and the theoretical framework is still evolving, with existing studies offering diverse and sometimes inconclusive insights.

3.4 Methodology

3.4.1 Research Context and Sample

With the urgency behind the need to accelerate innovations for various clean energy technologies to mitigate the impact of the global climate emergency through a rapid reduction in global greenhouse gas emissions, explaining the antecedents of successful innovation has become a topical research area of great interest. Nowadays, innovation projects are increasingly performed by teams of multiple inventors (see section 1.2). Scholars have hence invested significant efforts into finding those aspects in the composition of innovation teams that are associated with high-quality innovation outcomes. However, extant research has focused on the marginal effects of individual factors while paying little attention to the causally complex interplay of these factors. Moreover, the range of potential explanatory factors with respect to team composition is broad and – at least in parts – ambiguous (see Chapter 2). While a set-theoretic configurational analysis could add significant value to our understanding of successful team-based innovation, this theoretical landscape makes it inherently difficult to decide which factors to consider. Yet, it provides a topical research context to explore how these issues can be overcome. For that, I follow a substantial number of studies on innovation team composition that use patents as a proxy for innovation. While the validity of this practice has been discussed extensively in the scientific community (e.g., Acs & Audretsch, 1989; Griliches, 1990; Griliches et al., 1986; Kleinknecht & Reinders, 2012), patents have proven to be a well-quantifiable indicator for the development of knowledge across fields (e.g., Wuchty et al., 2007). Although a granted patent already indicates sufficient novelty and relevance to be labeled somewhat successful, there are significant differences in actual value for future developments among patents. Thus, for a configurational analysis of team-based innovation, each patent provides a *case* of innovation of certain quality, that is, at the same time, associated with specific characteristics of its inventor team. Based on these characteristics, for each patent, membership scores can be assigned for set membership in various sets of team composition related *conditions,* as well as for the observed innovation *outcome*, rendering publicly accessible patent data a well-suited foundation for my analysis.

To compile a dataset of team-based clean energy patents, I first collected 145,426 patents from ten core clean energy domains, based on their CPC codes[18]. My dataset includes patents that were granted by the *United States Patent and Trademark Office (USPTO)* from the beginning of 1980 and filed before the end of 2020. This includes 76,539 focal patents from the 1985-2015 period – and thus 30 years of innovation activity in the clean energy domain – as the main body of my analysis, as well as patents from the five-year periods prior to and after this time frame. 54,134 of the 76,539 focal patents were filed by teams, whereas 22,405 were

[18] The *Cooperative Patent Classification (CPC)* system is a joint effort of the USPTO and the EPO to harmonize patent classification. The CPC encompasses a detailed scheme with numerous (sub)classes and (sub)groups to assign codes to patents representing technological domains. CPC codes are not mutually exclusive – a patent is usually assigned multiple codes. The patents in the sample were identified based on the following subgroup-level codes: Y02E10/10 (Geothermal Energy – 170 Patents); Y02E10/20 (Hydro Energy – 540 patents); Y02E10/30 (Sea/Ocean Energy – 502 Patents); Y02E10/4X (Solar Thermal Energy – 1,747 Patents); Y02E10/5X (Photovoltaic Energy – 11,676 Patents); Y02E10/7X (Wind Energy – 2,812 patents); Y02E30/10 (Nuclear Fusion Technology – 294 Patents); Y02E50/X (Synthetic and Biofuels – 3,554 Patents); Y02E60/1X (Energy Storage – 21,671 Patents); Y02E60/3X and Y02E60/50 (Hydrogen Technology – 14,611 Patents). Note: there are some domain overlaps in the sample.

filed by lone inventors and are thus not considered for this analysis. I was able to obtain exhaustive data for >99% of the team-based patents, with 131 patents that I had to exclude from my analysis due to non-rectifiable data gaps. In addition, I leverage data from more than 1.65 million patents that were filed by the focal patents' inventors across all technological domains (not limited to clean energy) to calculate all measures described in the following section. I acquired the patent data via the *PatentsView* data analysis platform provided by the *USPTO's Office of the Chief Economist* and complemented the initial dataset with advanced data from the public *Google Patents* database as well as further secondary data sources to fill gaps in the data. PatentsView offers comprehensive data by using "a series of algorithms and post-processing techniques" to disambiguate inventors, assignees, and locations (Monath et al., 2021) that allows for the construction of measures for the majority of potentially relevant conditions synthesized through the systematic literature review presented in Chapter 2. I outline the applied measures for the outcome and conditions in the next section.

3.4.2 Outcome, Conditions, and Calibration

Existing studies on inventor team composition have linked a large collection of explanatory factors to various quality-related innovation outcomes. As the central aim of this dissertation is to shed light on the antecedents of those innovations that *shape and drive the trajectories* of key clean energy technologies, I focus on the *impact* of an innovation on future developments as the focal outcome. Innovation impact is by far the most commonly studied outcome in this context and is predominantly measured based on patent forward citations (see also Carpenter et al., 1981; Trajtenberg, 1990) in a particular period after a patent's publication (e.g., Huo et al., 2019; Vestal & Mesmer-Magnus, 2020). "Forward citations provide a good assessment of how the invention influences future research in a domain" (Boh et al., 2014, p. 350). Following this widely applied approach, I use the 5-year forward citations of a patent as a measure of innovation impact. More specifically, I first employ a negative binomial regression model to account for domain and year-specific idiosyncrasies:

$$Y_i \sim \text{NegativeBinomial}(\mu_i, \theta)$$

$$\log(\mu_i) = \beta_0 + \sum_{d=1}^{D-1} \beta_d \cdot \text{Domain}_d + \sum_{y=1}^{Y-1} \beta_y \cdot \text{Year}_y$$

In this model, Y_i represents the number of five-year forward citations for patent i, following a negative binomial distribution. The natural logarithm of predicted citations, $\log(\mu_i)$, is modeled as a linear combination of domain and year dummy variables, where β_0 is the intercept, β_d are the coefficients for domain dummy variables, and β_y are the coefficients for year dummy variables[19]. I then use the residuals as an adjusted measure for patent impact for subsequent steps.

Additionally, the systematic review of the literature on innovation team composition presented in Chapter 2 yielded a comprehensive list of team-level conditions that have shown to influence the impact of an innovation outcome. Many of these conditions can effectively be operationalized using patent data (Table 3.1). I created a bivariate correlation table (Table 3.2) to check for multicollinearity between these factors to avoid redundancy among causal conditions. While the pairwise correlations between the causal conditions and innovation impact are generally weak, some intercorrelations among the causal conditions are exceptionally strong. In particular, a large *prestige gap* frequently co-occurs with the presence of a *star inventor* on a team, as only a few teams consist solely of star inventors. Consequently, I excluded the prestige gap condition from the analysis. Additionally, the measures for *organizational diversity* and *inventor mobility* that can be derived from patent data are conceptually similar, both building on (past) patent assignees, resulting in redundancy between

[19] See Appendix 3.1 for the regression results.

Table 3.1: Measures and calibration details.

Outcome	Measure	Calibration Threshold(s)	Calibration Logic	
Innovation Impact (IMPACT_INNO)	5-year forward citations adjusted for domain and year idiosyncrasies	Fuzzy calibration[20]: e: 75th percentile c: 90th percentile i: 95th percentile (e.g., Chang, 2022)	Theory / Data distribution	
Condition	**Measure**	**Calibration Threshold(s)**	**Calibration Logic**	**Theoretical Effect on Outcome**
Knowledge Dissimilarity (KNOW_DIS)	Mean (cosine) distance between each team members knowledge vector calculated as centroid vectors of the document embedding vectors of each patent an inventor has filed	Inverse-U-shaped fuzzy calibration: e1: 10th percentile c1: 25th percentile i1: 33rd percentile i2: 66th percentile c2: 75th percentile e2: 90th percentile	Data distribution	*Positive / inverted-U shaped relationship:* some knowledge dissimilarity is required as impactful innovations have shown to be the result of novel combinations of distinct knowledge; if knowledge is too dissimilar, effective knowledge integration becomes more challenging (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020)
Knowledge Variety (KNOW_VAR)	Total number of all unique CPC subgroups assigned to the team members' prior patents, normalized by the number of team members	Fuzzy calibration: e: 25th percentile c: 50th percentile i: 75th percentile	Data distribution	*Positive effect:* Variety of technological knowledge broadens the pool of cognitive resources for novel cross-domain combinations (Huo et al., 2019; Zaggl & Pottbäcker, 2021)
Ethnic Diversity (ETHN)	Adjusted Blau's diversity index (Harrison & Klein, 2007) based on 4 ethnic groups inferred using the team members' last names[21]	Fuzzy calibration: e: 0 (no ethnic diversity) c: 0.25 (moderate diversity) i: 0.75 (significant diversity)	Data distribution / Reasoning	*Positive effect:* diverse ethnic backgrounds provide a greater variety of perspectives and access to a broader network (Freeman & Huang, 2014)
Gender Diversity (GEND)	Blau's diversity index (Blau, 1977) based on team members' inferred binary gender	Fuzzy calibration: e: 0 (male / female only team) c: 0.25 (moderate diversity) i: 0.4 (significant diversity)	Data distribution / Reasoning	*Lack of empirical insights*

[20] Although technically applying a fuzzy calibration here, I only use full members and full non-members to create more contrast in the outcome. Therefore, this can also be viewed as a crisp calibration with two thresholds.
[21] I use the *ethnicolr* Python module (https://github.com/appeler/ethnicolr) to infer ethnic groups based on US census data.

Geographic Dispersion (GEO)	Mean geodesic distance between team members' locations in km	Fuzzy calibration: e: 100 (single-region team) c: 500 (inter-regional team) i: 1000 (inter-national team)	Theory / Reasoning	*Positive / inverse U-shaped effect*: teams distributed over multiple countries create more impactful innovations (Kerr & Kerr, 2018); as geographic dispersion becomes too high, integration challenges outweigh the benefits from diverse location-bounds resources (Seo et al., 2020)
Institutional Diversity (INST)	Adjusted Blau's diversity index (Harrison & Klein, 2007) based on patent assignee types (individual, company, public institution) of team members' patents filed, including the focal patent	Crisp calibration: c: > 0 (at least one inventor brings experience from filing a patent with another institution type, or the focal patent is assigned to multiple institution types)	Data distribution / Reasoning	*Ambiguous effect:* innovating within the same type of institutional setting facilitates collaboration due to shared norms, incentives, and routines (Cassi & Plunket, 2014); academic inventors on a (corporate) team increase innovation impact (Czarnitzki et al., 2011)
Domain Experience (DOM)	Number of patents successfully filed by any team member that were assigned to one of the CPC subgroups assigned to the focal patent	Crisp calibration[22]: c: > 0 (at least one team member has filed a patent in the same domain in the past)	Data distribution / Reasoning	*Positive / inverted-U shaped relationship:* domain experience helps to effectively select relevant distinct knowledge pieces (Li et al., 2018; Schillebeeckx et al., 2019; Wang et al., 2017); high domain experience can cause cognitive rigidity hindering novel combinations (Wang et al., 2017)
Degree Centrality (DEG)	Mean number of team members' outside collaborations based on prior co-patenting, normalized by the total network size	Fuzzy calibration: e: 0 (no outside collaborations) c: 50^{th} percentile i: 75^{th} percentile	Data distribution / Reasoning	*Positive Relationship:* more ties to other inventors outside the team increase the inbound flows of ideas and expertise (Yang et al., 2021)
Gatekeeper (GATE)	Maximum betweenness centrality among team members, normalized by the total network size	Fuzzy calibration: e: 50^{th} percentile (below average betweenness centrality, clearly no gatekeeper) c: 66^{th} percentile (somewhat a gatekeeper on the team) i: 90^{th} percentile (clearly a gatekeeper on the team)	Data distribution / Reasoning	*Positive Relationship:* earlier, exclusive, and non-redundant information and knowledge help gatekeepers decide which technological trajectory to follow (Le Gallo & Plunket, 2020; Yang et al., 2021)

[22] The data distribution is highly skewed with most cases exhibiting no domain experience. I therefore use a crisp calibration although theory would also justify a fuzzy bell-shaped calibration curve to represent a curvilinear relationship with the outcome.

Organizational Diversity (ORG) *(Removed from the analysis due to high conceptual similarity with inventor mobility)*	Number of unique assignees of successful patent filings, including the focal patent, across all team members, normalized by the number of team members	-	-	*Ambiguous effect:* teams with diverse organizational backgrounds draw on a larger pool of resources and complementarity of roles (Singh & Fleming, 2010); multi-university collaborations tend to produce more impactful research (Jones et al., 2008); innovation for the same organization reduces transaction costs (Cassi & Plunket, 2014)
Prior Collaboration (PRICOL)	Number of prior pairwise collaborations between team members, normalized by the number of team members	Fuzzy calibration: e: 0 (no prior collaboration) c: 1 (members have worked with each other once on average) i: 2 (members have worked with each other twice on average)	Data distribution / Reasoning	*Ambiguous effect*: prior collaboration fosters impactful innovation through enhanced coordination capabilities and established routines but only if integrated knowledge is similar (Jiao et al., 2022); prior collaboration outside the focal domain diminishes innovation impact by developing context-specific practices (Onal Vural et al., 2013)
Team Size (SIZE)	Number of inventors on the focal patent	Fuzzy calibration: e: 3.5 (small team ≤ 3 members) c: 5.5 (medium sized team) i: 7.5 (large team ≥ 8 members)	Data distribution / Reasoning	*Ambiguous effect:* larger teams access broader networks and have greater visibility in the scientific community (Lee et al., 2015); large teams face greater coordination challenges (Wang et al., 2017); under some circumstances, smaller teams are associated with producing innovations that stimulate further research (Battaglia et al., 2021)
Generalist (GNRL)	Maximum number of unique CPC groups assigned to prior patents filed by a member of the team (i.e., maximum knowledge breadth of a single team member)	Fuzzy calibration: e: 50th percentile (below average knowledge breadth, clearly no generalist) c: 66th percentile (somewhat a generalist on the team) i: 90th percentile (clearly a generalist on the team)	Data distribution / Reasoning	*Ambiguous effect:* inventors with a broader knowledge base have higher capabilities to recombine previously disconnected ideas but the effect depends on the characteristics of the technological domain (Vakili & Kaplan, 2021)
Star Inventor (STAR)	Maximum number of successful past patent filings by any member of the team	Fuzzy calibration: e: 9.5 (clearly no star ≤ 10 prior patents, see Gay et al., 2008) c: 19.5 (rather a star with ≥20 patents, see Beaudry & Schiffauerova, 2011) i: 90th percentile	Theory / Reasoning	*Positive effect:* teams with star inventors benefit from their extensive expertise, integrative capacity, large network, and reputation (Gay et al., 2008)

Prestige Gap (PGAP) *(Removed from the analysis due to multicollinearity with the star inventor condition)*	Standard deviation of successful past patent filings across members of the team	-	-	*Positive effect:* teams with high productivity gaps benefit from efficient coordination, reduced conflicts, and mentorship, resulting from clearer hierarchical structures (Jiao et al., 2022)
Inventor Mobility (MOB)	Mean number of unique assignees of a team member's successful patent filings	Fuzzy calibration: e: 25th percentile c: 50th percentile i: 75th percentile	Data distribution	*Positive effect:* mobility fosters knowledge transfer and exploratory learning (Chang, 2022)
Recombination Novelty (RECOMB)	Mean number of novel co-occurrences of CPC subgroups in the focal patent based on subgroups assigned to each team member's past patents, normalized by all possible pairwise subgroup combinations	Fuzzy calibration: e: 0.25 (mainly familiar combinations, exploitation) c: 0.5 (half the combinations are novel to the team) i: 0.75 (mainly unfamiliar combinations, exploration)	Data distribution / Reasoning	*Lack of empirical insights*
General Experience (GEXP)	Median number of past successful patent filings among the team members	Inverse-U-shaped fuzzy calibration: e1: 1 c1: 5 i1: 10 i2: 15 c2: 20 e2: 90th percentile	Data distribution / Reasoning	*Positive / inverse U-shaped effect:* teams with moderate general invention experience are better at balancing exploration and exploitation, enhancing invention impact (Wang et al., 2017)

Table 3.2: Descriptive statistics.

	mean	std	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) 5-year Fwd. Citations (adj.)	-0.06	12.97	-																
(2) Knowledge Dissimilarity	0.57	0.42	0.02*	-															
(3) Knowledge Variety	7.48	3.35	-0.00	-0.33*	-														
(4) Gender Diversity	0.11	0.19	-0.01*	0.11*	-0.15*	-													
(5) Ethnic Diversity	0.24	0.31	0.00	0.09*	-0.01*	0.02*	-												
(6) Geographic Dispersion	525	1733	0.02*	-0.01*	-0.02*	0.01	0.04*	-											
(7) Institutional Diversity	0.07	0.14	0.02*	-0.00	0.08*	-0.00	-0.05*	0.05*	-										
(8) Prior Collaboration	2.37	9.51	0.02*	-0.09*	0.12*	-0.01*	0.01*	0.00	-0.03*	-									
(9) Team Size	3.57	1.77	0.04*	**0.80***	**-0.61***	0.19*	0.08*	0.00	-0.04*	-0.01	-								
(10) Degree Centrality	1.00E-04	1.44E-04	-0.02*	0.06*	0.10*	-0.02*	0.07*	-0.04*	-0.07*	0.18*	0.13*	-							
(11) Gatekeeper	2.52E-04	8.88E-04	-0.02*	0.10*	-0.00	0.03*	0.03*	0.02*	-0.01*	0.08*	0.13*	0.46*	-						
(12) Generalist	17.79	18.76	-0.01	0.37*	0.20*	0.00	0.08*	-0.03*	-0.06*	0.21*	0.23*	0.29*	0.26*	-					
(13) Domain Experience	0.15	1.12	0.02*	-0.04*	0.06*	-0.04*	-0.00	0.03*	-0.00	0.04*	-0.02*	-0.00	0.00	0.02*	-				
(14) Star Inventor	40.42	157.16	0.01*	0.07*	0.09*	-0.01*	0.02*	-0.02*	-0.04*	0.47*	0.06*	0.18*	0.14*	0.47*	-0.01	-			
(15) Prestige Gap	15.34	67.94	0.01*	0.05*	0.10*	-0.01*	0.02*	-0.02*	-0.04*	0.43*	0.03*	0.17*	0.13*	0.45*	-0.01*	**0.99***	-		
(16) Inventor Mobility	3.39	3.64	-0.02*	0.22*	0.27*	-0.04*	0.04*	-0.03*	-0.04*	0.12*	0.06*	0.21*	0.22*	**0.81***	-0.02*	0.33*	0.32*	-	
(17) Recombination Novelty	0.26	0.35	0.02*	-0.08*	0.15*	-0.01	0.03*	0.01	-0.03*	0.23*	0.05*	0.34*	0.14*	0.17*	0.07*	0.11*	0.09*	0.10*	-
(18) General Experience	13.16	55.48	0.00	-0.04*	0.20*	-0.03*	0.01	-0.01*	-0.03*	**0.61***	-0.05*	0.18*	0.09*	0.31*	0.01	**0.73***	**0.75***	0.27*	0.13*

Note: Statistically significant pairwise correlations ($p < 0.05$) are marked with an asterisk (*). Strong pairwise correlations (> 0.6) are highlighted in bold font.

these two conditions. Therefore, organizational diversity was likewise removed from the analysis.

Furthermore, to assign set membership to a case for the outcome and each of the causal conditions, QCA scholars use a calibration process for which they must define calibration thresholds. When using *crisp* (i.e., dichotomous) calibrations, a sharp line is drawn at the threshold where set membership begins or ends. In contrast, *fuzzy* calibration allows cases to be fully in or fully out of a set, or to belong to a set to only a certain degree. For some of the conditions described above, I use crisp calibrations, while for others, I employ fuzzy sets[23]. Moreover, for certain conditions, a theoretical basis is available to inform the definition of calibration thresholds. However, for most conditions (and for the outcome), there is a lack of external standards to guide the calibration process, requiring to turn to the distribution of the data itself. Table 3.1 provides the complete list of conditions considered, including short descriptions for the measures used, the calibration logics and thresholds applied, and the underlying theoretical reasoning regarding their effects on the innovation impact. Additionally, in Table 3.1, I introduce abbreviations for the outcome and the conditions that I will continue to use throughout this and the following chapter.

3.4.3 Model Comparison

To find the combination of conditions (i.e., the model specification) that, in conjunction, are best suited for explaining how inventor teams that produce particularly impactful innovations are composed, I compare the solutions of truth table minimizations for *all possible combinations of conditions*. Although certain sources suggest a maximum of seven conditions to maintain the interpretability of results (e.g., Marx, 2010), I utilize a more flexible range of four to eight conditions when composing the models for comparison. With

[23] I use the QCA R Package (Duşa, 2019) for all calibrations, truth table constructions, and minimizations.

$$\binom{N}{k} = \frac{N!}{k! \cdot (N-k)!}$$

unique combinations and thus possible model specifications for k chosen conditions from a total of N potential conditions without replacement, this leads to 1820 different models with four conditions, 4368 models with five, 8008 models with six, 11440 models with seven, and 12870 models with eight conditions. For each of these 38,506 models, I assess the model performance based on the consistency and coverage of the complex solution[24] as the result of the truth table minimization. For each minimization, I use a consistency cutoff of 0.8, a PRI cutoff of 0.7, and a 1% frequency cutoff[25]. Instead of running the QCA on the full sample of 54,003 cases only once, I randomly create 20 balanced samples[26] (n = 200) by selecting 100 cases that fully belong to the set of impactful innovations (calibrated outcome = 1) and 100 cases that are fully out of the set of impactful innovations (calibrated outcome = 0). This approach has several advantages: First, impactful innovations are by definition (here: top 5% in forward citations) a rare outcome (Capponi et al., 2022), imposing a strong barrier to consistent findings. This is because QCA relies on the comparison of combinations of conditions across positive and negative outcome cases to establish a clear contrast between configurations that are associated with impactful innovations and those that are not. This issue is accounted for by using a balanced sample of an equal number of cases that clearly do and those that do not exhibit the outcome of interest (Miric & Fiss, under review). Secondly, comparing the performances of models for a single version of the full sample might lead to the identification of a model that is strongly overfitted to the exact characteristics of the sample with little robustness to deviations from this particular "truth". I address this issue by using the lower bounds of the 95% confidence intervals for solution consistency and coverage across all 20 runs to evaluate the model performances. More specifically, I only consider models that find

[24] Different solution types in QCA are explained in more detail in section 4.5.2.
[25] An in-depth explanation of these cutoffs is provided in section 4.4.2.
[26] I chose the number of samples as 20 to maintain an acceptable quality of the model performance estimates at reasonable computational costs. A larger number of samples may further increase the accuracy of the confidence intervals but at diminishing returns.

a consistent solution in at least 95% of the 20 runs[27] and that have a lower bound value of the 95% confidence interval for their solution *consistency* of at least 0.8. I then use the lower bound value of the 95% confidence interval for each model's solution *coverage* as the primary measure for model performance – as "coverage gauges empirical relevance or importance" (Ragin, 2008, p. 44) – to rank the models based on the fraction of highly impactful innovation cases they explain. Finally, I select the 20 best-performing (i.e., highest solution coverage) models for each number of conditions for a subsequent clustering based on similarity of conditions used in the models to identify combinations of conditions that are commonly shared among the best-performing models. The notion behind this approach is that conditions that consistently appear among the best-performing models are more likely to reflect the true underlying causal relationships that explain impactful innovations. In contrast, focusing on the single best-performing model entails the risk that conditions appear important because of sample peculiarities, noise, or merely by chance, potentially leading to a "house-of-cards-model" that explains the phenomenon well only as long as no condition is added, removed, or substituted. Figure 3.1 summarizes the full model selection procedure.

3.5 Findings

3.5.1 Model Performance

The results show that the mean solution consistency, coverage, and success rate across all models increases with the number of conditions included (Figure 3.2). While the mean solution consistency is exceptionally low for four conditions, the situation is precisely the opposite when considering only the models that lie above the defined thresholds (solution consistency ≥0.8; success rate ≥95%). The reason for that lies in the small number of models that pass the

[27] Depending on the cases selected in the random balanced sampling procedure, there may not be a consistent solution for a model. By selecting a 95% threshold for models to be considered as well-performing, I allow for 1 out of 20 runs that could have created a sample that yielded no consistent solution by chance.

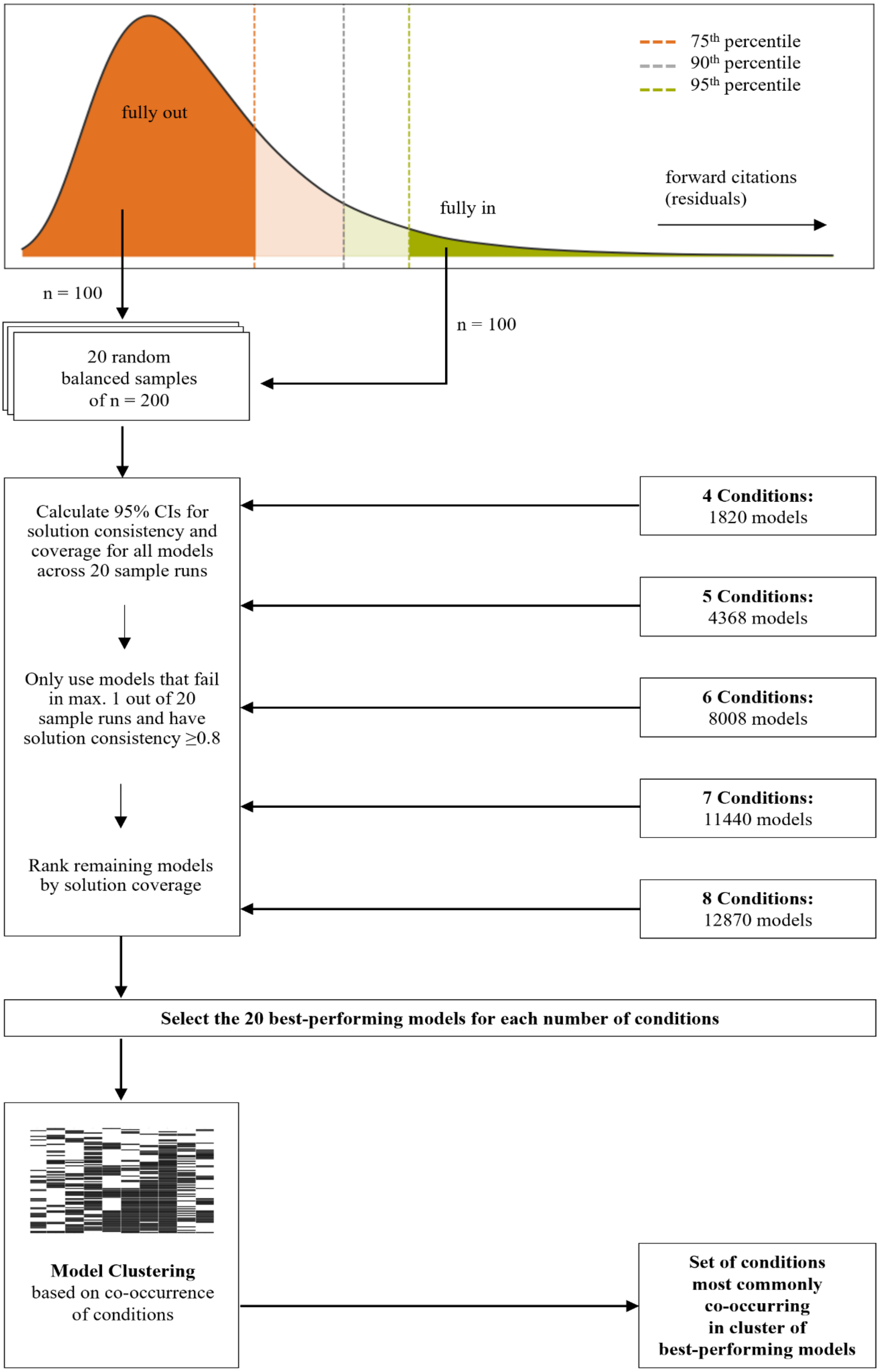


Figure 3.1: Model selection procedure.

success rate threshold: With only four conditions, all 200 cases are assigned to just 16 possible configurations (i.e., truth table rows). In that situation, there is little opportunity to catch differences between cases that exhibit the outcome and those that do not. Hence, most runs fail without finding any consistent solutions that explain these differences. With only four conditions, passing the 95% success rate threshold remains a rare exception (<1% of the

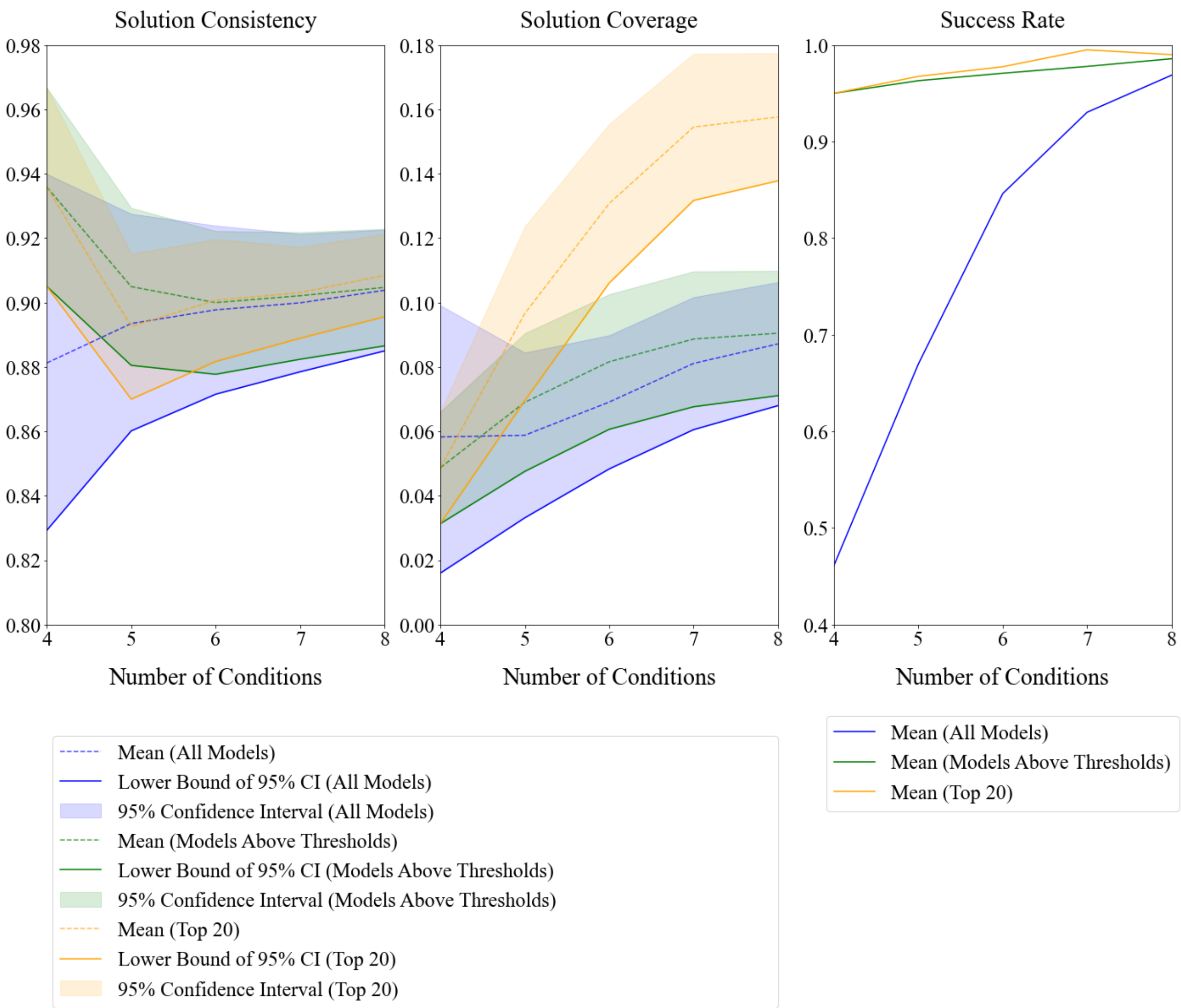


Figure 3.2: Model performance overview.

models) that only occurs in conjunction with exceptionally high solution consistency. With more conditions added, the mean solution consistency and the fraction of models that reliably find consistent solutions show an increasing but converging pattern. Hence, more and more models have sufficient success rates, and it is not just the exceptionally consistent outliers anymore that determine the mean solution consistency among the models that make it past the thresholds, leading to a drop in solution consistency among them.

The solution coverage illustrates a clear trend, with a gradual but diminishing increase as more conditions are incorporated. With each condition, complexity is added to the model at the cost of parsimony, allowing for a more nuanced distinction between configurations and, thus, cases. A case of impactful innovation that would not have been explained by a smaller number of conditions now may be clearly distinguishable from a non-impactful innovation case that is similar in most other conditions, leading to a higher fraction of outcomes consistently explained by the model. At some point, however, adding more conditions will barely reveal any additional rare configurations, resulting in a convergence of the solution coverage. This holds true for the best-performing models (i.e., model with the highest solution coverage), as there is very little improvement with eight compared to seven conditions.

3.5.2 Model Clustering

Following the identification of the best-performing models based on their solution coverage, I perform a clustering across the 20 best-performing models for each number of conditions, using the intersection of conditions in relation to the overall number of unique conditions among two models as a similarity measure[28, 29]. I then use the largest pairwise distance between two models as the determining method to derive clusters[30]. This represents a rather conservative approach as models are assigned to the same cluster only if they have a large overlap in their conditions.

Figure 3.3 shows the emerging model clusters ordered by the number of conditions in the models. Interestingly, *institutional diversity* appears to be a key building block for the vast

[28] For four conditions, only 13 models exceed the thresholds, leading to a total of 93 instead of 100 models considered in the clustering.
[29] Using *Jaccard* distance: "Given two vectors, u and v, the Jaccard distance is the proportion of those elements u[i] and v[i] that disagree." *(https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.distance.pdist.html#scipy.spatial.distance.pdist)*
[30] Using the *complete* linkage method, calculating the maximum pairwise distance between all points in two clusters. *(https://docs.scipy.org/doc/scipy/reference/generated/scipy.cluster.hierarchy.linkage.html#scipy.cluster.hierarchy.linkage)*

majority of the best-performing models and is present in every single one of the top 20 models with six or more conditions. *Ethnic diversity* and *gender diversity* play a similarly important role, especially in more complex models as well. In contrast, *team size* appears in only one of the best-performing models. All but one of the models with only four conditions share *domain experience* as a common factor. However, as soon as another condition is added, domain experience seems to not be a driver for high model performance any longer, highlighting how a well-performing but unstable model (or a small set of models) gives little robust causal explanation of the phenomenon. It is therefore advisable to turn to the most pronounced cluster (dashed line) that extends over a broad range of models with varying complexities. With *institutional diversity*, *ethnic diversity*, and *gender diversity* at its core, the cascading structure of the cluster suggests *knowledge dissimilarity*, *recombination novelty*, and *degree centrality* as additional conditions that are prevalent among similar well-performing models, with the latter three conditions in descending order with respect to co-occurrence. This cascading structure suggests a hierarchy in the importance of conditions for explaining impactful innovations.

In Figure 3.4, I demonstrate that starting with the four conditions that most often occur together in the best-performing models – namely *institutional diversity*, *ethnic diversity*, *gender diversity,* and *knowledge dissimilarity* – and moving up the cascading structure of the cluster, by adding additional conditions (*recombination novelty* and *degree centrality*), improves the quality of the model both in terms of absolute consistency and coverage, as well as relative to other model specifications with the same number of conditions. While the four most central conditions alone seem to be insufficient to explain the differences between teams associated with impactful innovations – this is in line with the aforementioned finding that models with four conditions rely on *domain experience* as a differentiating factor – adding the fifth and next-closest condition from the cluster (*recombination novelty*) already leads to above-average model performance. For seven (adding *inventor mobility*) and eight conditions (adding

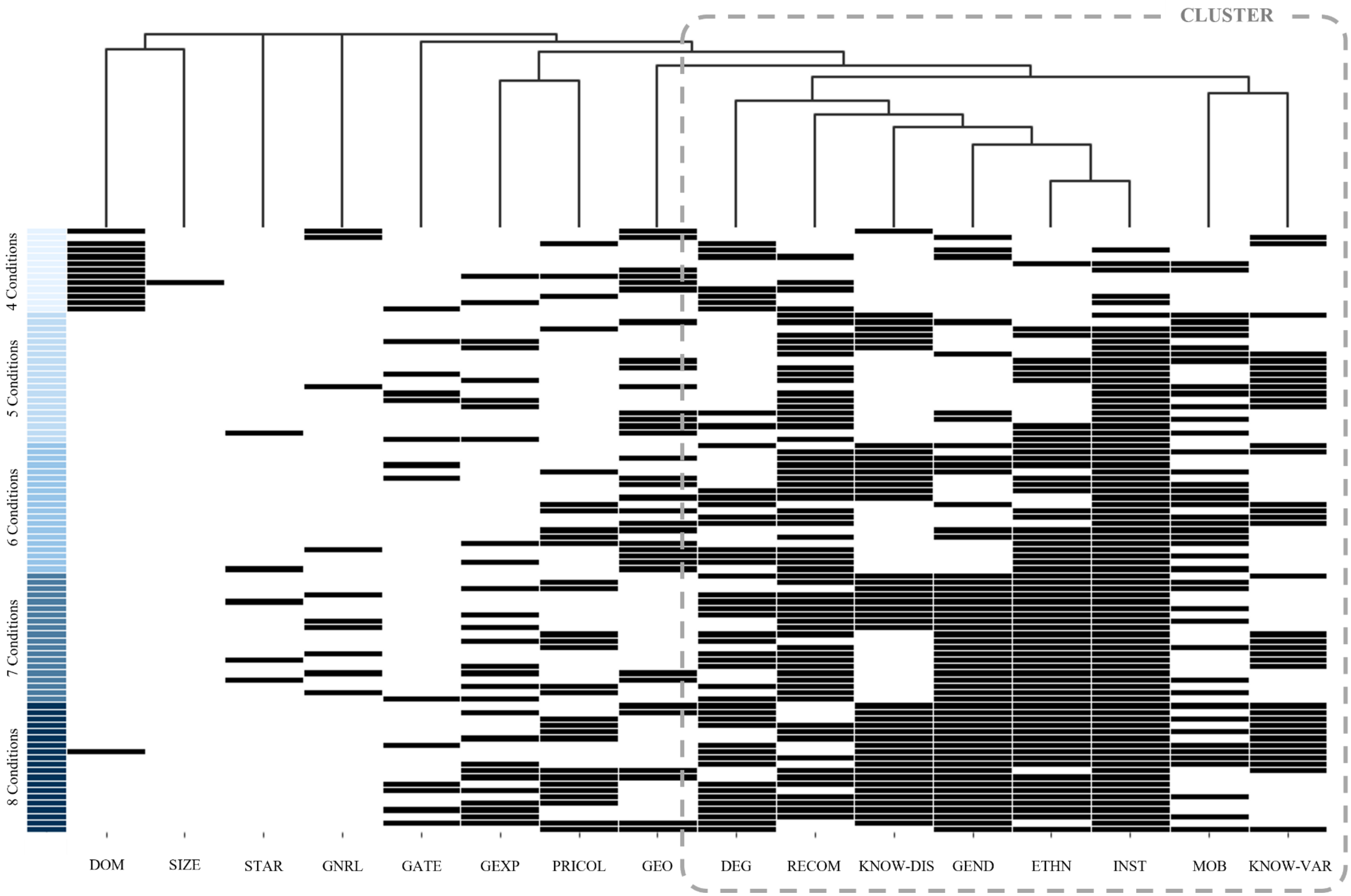


Figure 3.3: Model clustering.

knowledge variety) from the focal cluster[31], the model outperforms almost any other model with the same number of conditions. For seven conditions, there are only three models, and for eight

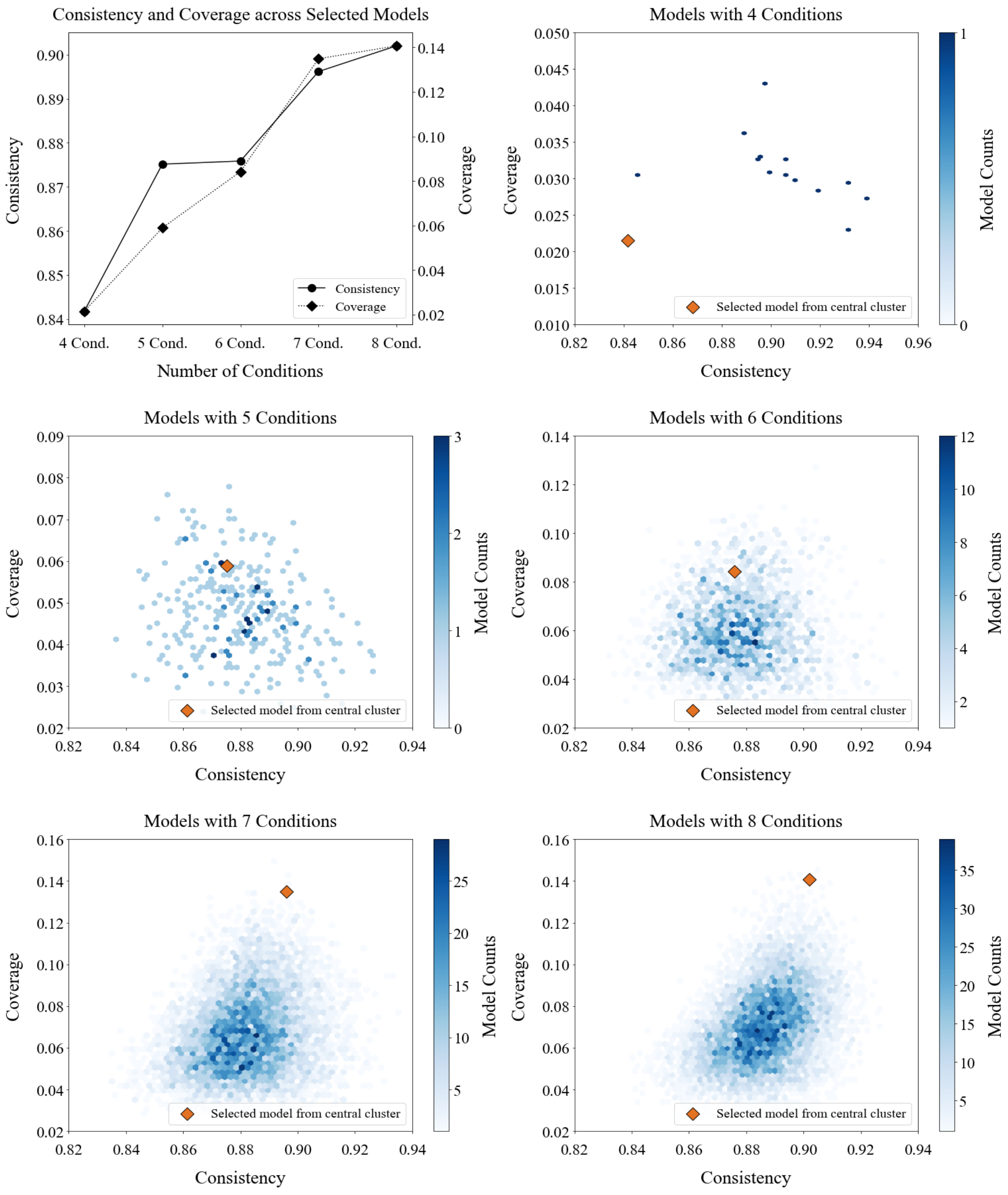


Figure 3.4: Model performance comparison.

[31] *Inventor mobility* and *knowledge variety* have equal distances to the core of the cluster when using the conservative "complete" linkage method. However, when using "average" linkage (see Appendix 3.1), inventor mobility has the smaller distance, making it the seventh and knowledge variety the eighth condition following the cascading structure of the cluster.

conditions only four models that yield higher model performance with respect to coverage. Overall, only six out of the total 38,506 possible model specifications (0.016%) explain more of the differences between team configurations that are associated with impactful innovations and those that are not than the model that combines the eight conditions from the highlighted cluster (see Appendix 3.3). Most notably, all of these six even better-performing models share the four most commonly co-occurring conditions and deviate from the cluster by at most a single condition (in the better-performing models with seven conditions) or two conditions (in the better-performing models with eight conditions). In summary, the combination of conditions identified through clustering the best-performing models based on co-occurrence of conditions reveals a set of conditions that, in combination, are likely causally relevant in explaining the difference between team configurations that yield particularly impactful innovations and those that do not.

3.6 Robustness Tests

To ensure the reliability of the findings, it is crucial to assess whether they hold under various conditions. For that reason, I apply multiple sensitivity tests (see Appendix 3.4) to assess the consistency of the findings when key parameters are altered. First, I test different consistency thresholds. Instead of using 0.8 as a threshold for including a model, I use 0.85 and 0.9 as an even stricter criterion. At a consistency threshold of 0.85, there are no notable changes to the emerging cluster of central conditions. For 0.9, *geographic dispersion* and, to a less pronounced degree, *general experience* and *prior collaboration* gain relevance. These are the same conditions that predominantly appear as a substitution for one or two conditions in the few models that outperform the combination of conditions from the original cluster. At the same time, the original set of key conditions remains prominent, indicating that the central cluster is fairly robust even under stricter criteria. For a less stringent consistency threshold of 0.7, no changes appear compared to the original clustering output. Next, I alter the success rate threshold. When only considering models that provide consistent results for all 20 random subsamples (success rate = 1), there is no model composed of four conditions that passes the criteria. However, the emerging central cluster remains stable[32]. Using a less restrictive success rate threshold of 0.8 has no impact on the emerging cluster.

To further assess robustness, I examine the effects of changing the number of models considered in the clustering from the 20 best-performing models per number of conditions to only the top ten models with respect to coverage. This adjustment results in no significant changes, except for a slight increase in the relative distance of *inventor mobility* from the rest of the central cluster. Similarly, I re-run the clustering for the 30 best-performing models[33] for each number of conditions. As a result, *geographic dispersion*, *general experience*, and *prior collaboration,* again, co-occur more frequently with the other conditions from the original cluster.

Finally, I repeat the entire approach with different sizes for the balanced random samples[34]. Instead of a total of 200 cases, I randomly select 100 cases and 500 cases respectively. Interestingly, using fewer cases (in relation to the number of conditions and thus possible configurations) leads to a notable increase in average model consistency, coverage, and fewer unsuccessful truth table minimizations (i.e., higher success rates). Conversely, for the larger samples of 500 cases, truth table minimizations using the previously employed consistency cutoff of 0.8 and PRI cutoff of 0.7 barely yield any solutions due to a drop in consistency. Only after decreasing the cutoff values to 0.7 for consistency and 0.6 for PRI do the minimizations provide solutions for a reasonable number of model specifications to perform a subsequent clustering. While *institutional diversity*, *ethnic diversity*, *gender diversity*,

[32] This is the case when "average" is used as the less conservative cluster linkage method. Using "complete" shows some differences, such as *general experience* becoming more relevant again. For more information on cluster linkage methods see footnote 30 in section 3.5.2.

[33] Again, for four conditions, only 13 models exceed the thresholds, leading to a total of 143 instead of 150 models considered in the clustering.

[34] While maintaining a frequency cutoff of 1% for the truth table minimizations.

knowledge dissimilarity, and *inventor mobility* remain parts of the central cluster, *geographic dispersion*, *prior collaboration*, and having a *gatekeeper* on the team co-occur more often with these conditions and appear to be similarly relevant to *degree centrality*, *knowledge variety*, or *recombination novelty*.

3.7 Discussion

While QCA is technically capable of handling a large number of causal conditions in a model, there is a practical limit as findings become much more difficult to interpret as the number of conditions increases (Greckhamer et al., 2018; Greckhamer et al., 2013). When performing QCA in a large-N setting, researchers cannot maintain close familiarity with each individual case, which naturally increases the "distance" to the cases (Greckhamer et al., 2013; Rutten, 2022). This reduced case familiarity makes it significantly more difficult to leverage in-depth case knowledge when identifying the most relevant conditions to explain the outcome of interest. Moreover, scholars commonly turn to the literature to derive a theory-based specification of the QCA model. However, some theoretical landscapes are composed of many more factors that could potentially be considered along with sparse or inconsistent insights into which of these factors matter most to explain the outcome. Against this background, in this chapter, I introduced a novel data-driven approach that systematically evaluates all possible combinations of conditions and identifies those that most frequently co-occur in the best-performing models. By focusing on conditions that consistently appear across multiple high-performing models, this method helps to uncover factors that, when combined, are likely to have genuine causal significance.

By clustering the conditions appearing in the best-performing models, I identify a robust set of factors that appear to play a fundamental role in the configurational antecedents of innovation teams producing highly impactful clean energy innovations. Specifically, *institutional diversity*, *ethnic diversity*, *gender diversity*, and *knowledge dissimilarity* emerged at the core of the central cluster. The prominence of institutional diversity suggests that teams composed of inventors who work or have worked in different types of organizations may contribute to higher innovation impact, possibly due to the integration of varied organizational practices and resources (Czarnitzki et al., 2011), even when conjunctural effects are considered. Similarly, the prominence of ethnic and gender diversity suggests that demographic aspects play a central role. Literature shows that demographic heterogeneity increases cognitive diversity (Choudhury & Kim, 2018; Marino & Quatraro, 2022) and allows a team to draw on a greater variety of perspectives (Freeman & Huang, 2014). Knowledge dissimilarity within teams potentially fosters impactful innovations by enabling the utilization of diverse and non-obvious combinations of existing knowledge, thereby expanding the search space for novel solutions and increasing the likelihood of groundbreaking advancements (Fleming, 2001; Uzzi et al., 2013). Yet, it is important to note that, without an in-depth configurational analysis, at this point, there is no indication whether and how the presence or absence of any of these conditions links to impactful innovations. The robustness checks performed confirmed that these central conditions remain consistently prominent across various sensitivity analyses, indicating the stability and reliability of the findings. The findings also illustrate that, by following the cascading structure of the identified cluster of relevant conditions, adding conditions such as *recombination novelty* and *degree centrality* significantly improved model performance in terms of solution consistency and coverage. Considering the practical limit to the number of conditions that can reasonably be included in a QCA study and recognizing the diminishing returns in model improvement when adding the eighth most co-occurring condition, the presented approach suggests a model that balances parsimony and explanatory power, composed of the following seven conditions: *institutional diversity*, *ethnic diversity*, *gender diversity*, *knowledge dissimilarity*, *recombination novelty*, *degree centrality*, and *inventor mobility*. Interestingly, while some of these conditions, such as knowledge dissimilarity, have been studied extensively in the context of innovation impact individually, others, like recombination novelty, have received little attention in the extant literature. Conversely, *team size*, despite being a commonly studied factor, did not emerge as a central condition for teams to create impactful innovations.

3.7.1 Contributions

With the novel methodological approach introduced in this chapter, I provide QCA scholars with a systematic and replicable method to identify the most relevant conditions for explaining the outcome of interest, particularly in large-N studies where theoretical guidance may be limited and case familiarity is low. While this approach was specifically developed to address the challenges of complex theoretical settings – characterized by numerous potential factors and limited insight into their relative importance – it can also help address common criticism regarding the lack of clear justification for the selection of certain conditions over others in QCA studies more broadly. This aligns with the trend of complementing the traditional QCA process with other methodological approaches to combine their respective strengths (e.g., Haynes, 2014; Meuer & Rupietta, 2017; Rupietta & Meuer, 2024). The proposed method enhances the robustness and reliability of the analysis, focuses on conditions that likely demonstrate genuine causal significance, and, thus, increases confidence in the findings. As QCA is more broadly applied across various research domains and the trend towards large-N settings intensifies, this approach represents a significant and timely contribution to the development of QCA.

3.7.2 Limitations and Future Research

Despite the value added by the proposed method, it is not without limitations. First, evaluating all possible combinations of conditions is computationally intensive. The computational resources required increase with the number of potential conditions, the number of random samples used to calculate confidence intervals for solution consistency and coverage, and the number of cases used in each sample. However, these limitations become minor obstacles when high-performance computing resources are available. Moreover, although robustness checks help reduce the risk of overfitting the resulting model to the specific dataset, generalizing findings beyond the dataset must be approached with caution. Complementing the findings from this data-driven approach with rigorous theoretical insights can enhance confidence and improve the generalizability of the results. Additionally, this method was developed and tested within a single research context (i.e., innovation teams in clean energy technologies). Future research should validate the proposed approach in different domains. Additionally, further development of this method could focus on algorithmic optimization to minimize the reliance on expensive computational resources.

4. A Set-Theoretic Analysis of Innovation Team Configurations

This chapter introduces a configurational perspective to abductively explore how various team composition factors interact to influence the impact of the innovation outcome. Drawing on configurational theory, I complement traditional bivariate methods that predominantly examine individual factors in isolation and, instead, take aspects of causal complexity, such as conjunctural causation, equifinality, and causal asymmetry into account. Using set-theoretic methods, specifically Qualitative Comparative Analysis (QCA), I conduct a (very) large-N analysis based on thousands of clean energy patents to identify team configurations (i.e., causal pathways) associated with impactful innovations in the clean energy sector.

4.1 A Configurational Perspective

Innovation management scholars have examined a wide range of team composition factors and how they influence the impact a team's innovation outcome has on subsequent technological developments. For instance, various studies have shown that teams produce particularly impactful innovations when the differences in knowledge held by the inventors on a team is moderate, while similar and exceptionally distinct knowledge bases tend to yield less impactful outcomes (e.g., Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022). Other studies show that it is particularly beneficial if some members of the team bring prior experience innovating in the focal field to the table (e.g., Li et al., 2018; Schillebeeckx et al., 2019). While these works provide valuable insights into the antecedents of successful team-based innovation, most research to date – with only very few exceptions (e.g., Battaglia et al., 2021) – predominantly follows the classical approach of "causally isolating […] factors" (Miric & Fiss, under review, p. 1) through the application of bivariate methods that focus on marginal impact. However, considering that, in reality, team attributes do not exist in isolation but are embedded in a "multidimensional constellation of conceptually distinct characteristics that […] occur together" (Meyer et al., 1993, p. 1175), applying a theoretical perspective that acknowledges the configurational nature of innovation team composition appears both important and valuable.

Configurational theory captures the *complex causal interactions* between multiple individual factors: A team may consist of generalists or specialists, or a mix of both, while its members vary in their levels of innovation experience, from extensive to none, and, at the same time, exhibit distinct demographic characteristics. While correlational approaches help determining, for example, the relative contribution of any single such team attributes to the likelihood of producing highly impactful innovations, understanding how factors synergistically combine to jointly determine the innovation outcome (*conjunctural causation*) calls for a different view (Fiss, 2007). Moreover, when, instead, applying a configurational lens, the assumption of all cases of impactful innovations following the same causal pathway – which is implied in the use of common regression-based methods – is challenged as configurational theory allows for multiple causal recipes to be equally viable (*equifinality*) in achieving the desired outcome (Y. Park et al., 2020; Ragin, 2000, 2008). This seems quite plausible for configuring innovation teams as well: There is little reason to believe that there is only one particular way to set up a team for success. Extending the underlying notion of equifinality, Fiss (2011) introduced the concept of the causal core and periphery of configurations. This idea suggests that "within any given configuration, more than one constellation of different peripheral causes may surround the core causal condition, and the permutations do not affect the overall performance of the configuration" (Fiss, 2011, p. 398). Accordingly, in the context of innovation, some team attributes may be key building blocks for creating impactful innovations, while others may be substitutable (Misangyi & Acharya, 2014) or even irrelevant in some combinations, leading to a multitude of eligible team configurations. Furthermore, configurational theory acknowledges *asymmetry* in causal mechanisms: While correlations suggest that the variation of an explanatory variable causes the outcome to shift in one direction, it simultaneously implies that a variation in the opposite direction leads to a corresponding change in the outcome. From a configurational point of view, however, if one team attribute is commonly associated with highly impactful innovations, its absence does not necessarily have to be linked to less impactful outcomes or can even be associated with impactful innovations as well. One causal pathway that is linked to impactful innovations may include pronounced demographic diversity within a team, providing the team with a greater pool of beliefs and perspectives to draw on (Nielsen et al., 2018). Yet, the tendency of more demographically diverse teams to experience elevated levels of conflict (Jehn et al., 1999; Nishii, 2013) may impair a team's innovation capabilities when combined with, for example, large differences in expertise that require a certain integrative capacity that allows for the reconciliation of diverse knowledge and perspectives (Dougherty, 1992) and for overcoming the coordination costs as a concomitant of input diversity (Bercovitz & Feldman, 2011). Thus, embracing configurational theory allows us to move beyond isolated factor analysis and embrace the complex causal mechanisms inherent in innovative teams.

4.2 Set-Theoretic Methods and QCA

While conventional bivariate methods often struggle to capture the intricate interplay of factors in causally complex phenomena, set-theoretic methods offer an analytical toolbox tailored to address these research challenges (Fiss, 2007; Ragin, 2000, 2008) by applying a configurational view on causality (Mithas et al., 2022). "As such, set-theoretic methods differ from conventional, variable-based approaches in that they do not disaggregate *cases* into independent, analytically separate aspects but, instead, treat configurations as different types of cases" (Fiss, 2007, p. 1181). Applying this logic, each case can be described by its *set memberships* for each attribute (and the outcome of interest) that – in their sum – make that case representative of a particular configuration (i.e., combination of attributes). In the context of innovation team composition, consider a team-based innovation project as one single case that yields a technological development with a certain impact on future innovations. The respective innovation team is characterized by various compositional attributes, such as, for instance, team size or demographic diversity. Assuming a team is composed of seven members of which all but one are female, that team could then be classified as, for example, a large team (i.e., has membership in the set of large teams) and simultaneously not gender-diverse (i.e., has no membership in the set of gender-diverse teams). The same idea can be applied to the observed outcome, determining whether a case belongs to the set of impactful innovations. In set-analytics, the cases are then used to derive subset relationships. For instance, one could observe that cases with gender-diverse teams are also commonly cases that yield an impactful innovation outcome. In set-theoretic terms, gender-diverse teams can then be expressed as a subset of the teams that create impactful innovations. This way, such logical statements about the relationship with the outcome can be made for any single attribute or any combination (i.e., configuration) thereof. Furthermore, on that basis, an attribute (or combination of attributes) could be found to be either necessary – meaning that there is no configuration associated with the outcome that does not contain that particular attribute (or combination of attributes), or sufficient – meaning that any configuration containing that attribute (or combination of attributes) is associated with the outcome (Mackie, 1974).

With *Qualitative Comparative Analysis (QCA)*, introduced by Ragin (2000, 2008) and further developed by a growing community of scholars since, set analytics have become well-adopted across various scientific fields. In management research specifically, QCA has been used to, for example, explain how configurations of regional entrepreneurial ecosystems are linked to high-performing startups (Vedula & Fitza, 2019), or how country-level institutional factors influence executive compensation (Greckhamer, 2016).

In QCA, a truth table is constructed, containing all possible combinations of conditions[35] (i.e., configurations) that specify the different types of cases. For each case, set memberships for all conditions and the outcome are determined following a calibration procedure based on calibration thresholds defined by the researcher. As a result, each case represents a specific configuration (i.e., row in the truth table). There may be multiple cases that correspond to the same configuration. Such cases have very similar characteristics and, thus, show the same (or similar degrees of) set membership. In a subsequent step, the truth table is minimized using an algorithm (*Quine-McCluskey*)

[35] While the broader term "attribute" was used earlier in this section to describe general factors in the context of set-theoretic methods, it will now be replaced by the more precise QCA terminology.

based on Boolean algebra. To illustrate how this logical reduction is achieved[36], assume two configurations with an arbitrary number of cases and both configurations vary in only one condition while consistently featuring the observed outcome. This would mean that the condition in which these two configurations are distinct would be irrelevant for explaining the outcome as both the cases that exhibit this condition as well as those that do not lead to the same result. For innovation team composition, this could mean that, for example, teams that are geographically dispersed and those that are in the same location (i.e., members and non-members of the set of geographically dispersed teams) both are equally associated with producing highly impactful innovation outcomes. Thus, the condition of geographic dispersion provides little insight into the antecedents of successful team-based innovation. In the following sections, I apply QCA for a set-theoretic analysis of innovation team composition to identify those configurations that are associated with producing exceptionally impactful innovations and thus drive technological trajectories.

4.3 Team-Level Antecedents of Impactful Innovation

To identify the causal configurations among innovation team compositions associated with impactful innovations, it is essential to select a relevant set of conditions. While Chapter 2 reveals an extensive list of team composition factors influencing innovation outcomes, there is a practical limit to the number of conditions that can be included in QCA, due to increasing interpretative difficulties as more conditions are added. To address this challenge, Chapter 3 introduces a novel approach for selecting causally relevant conditions that is tailored to the characteristics of the theoretical landscape of research on innovation team composition. Hence, by clustering the best-performing QCA models, I synthesized a set of seven conditions that, in conjunction, appear to reliably explain a significant proportion of cases yielding impactful innovations: *institutional diversity*, *ethnic diversity*, *gender diversity*, *knowledge dissimilarity*, *recombination novelty*, *degree centrality*, and *inventor mobility*.

[36] This is just one example for how this reduction works. There are other aspects to it that are – in parts – introduced later in this chapter.

Institutional diversity within a team has emerged as the most central condition from the analysis in the previous chapter. However, the literature presents differing views on the effect of institutional diversity among team members on the impact of the innovation outcome. Cassi and Plunket (2014) conclude that it is beneficial for team members to have previously patented under the same type of institutional setting – either corporate or public institutions. They argue that successful collaboration relies on shared norms, incentives, and routines, which are deeply rooted in the operational logics of different institutional types. In contrast, Czarnitzki et al. (2011) demonstrate that the participation of an academic inventor leads to higher-impact innovations, despite the inherent differences between university settings and private companies. For example, in academia, the prospect of publication often serves as a greater incentive than monetary profit. These contrasting findings suggest that the role of institutional diversity in innovation teams is complex and may depend on combined effects with other conditions.

Ethnic diversity and *gender diversity* as demographic aspects of team composition appear next in line among the most relevant conditions. Although demographic diversity is one of the most frequently studied factors in innovation team research, there is a notable scarcity of literature specifically addressing the effect of team-level gender diversity on innovation impact. While some evidence supports the notion that "[research] teams with members from diverse ethnic backgrounds may benefit from a greater variety of perspectives" and access to a broader network (Freeman & Huang, 2014, p. 305), leading to more impactful publications, one can only infer – based on studies from adjacent research contexts (e.g., Díaz-García et al., 2013; Garcia Martinez et al., 2016; Østergaard et al., 2011) – that this mechanism applies to gender diversity in a similar way.

Conversely, for *knowledge dissimilarity*, a solid empirical foundation exists. Various studies have shown an inverted U-shaped relationship between the (dis)similarity of knowledge and expertise held by the inventors and the likelihood of creating impactful technological advancements (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020). Some difference in knowledge bases among the inventors is required to create fruitful outcomes. This idea follows the common line of argumentation in the literature that innovations are the result of novel combinations of acquainted but distinct knowledge (Carnabuci & Operti, 2013; Fleming & Sorenson, 2004; Hargadon & Sutton, 1997; Henderson & Clark, 1990; Usher, 1954; Uzzi et al., 2013). This also provides support for *recombination novelty* – the degree to which an innovation builds on different areas of expertise that are novel in their combination, and thus exploratory, to the inventors of a team – as another relevant condition to be considered. However, when the knowledge among team members becomes too dissimilar, a team is more likely to lack the necessary levels of integrative capacity so that "the transaction and coordination costs may become detrimental to innovative performance" (Cassi & Plunket, 2014, p. 400). While a certain diversity and wealth of inputs seems essential, Harvey (2014, p. 325, 337) argues that it is the process of "creative synthesis" that determines the chances of developing impactful innovations by creating a "shared understanding of the problem", "combin[ing] […] cognitive, social, and environmental resources", and "evaluating the constituent ideas to identify relationships between them". Nevertheless, access to various inbound flows of ideas and expertise can be highly beneficial. Teams with high *degree centrality* and, thus, a central position in the greater network of collaborating inventors (i.e., teams with numerous ties from past collaborations to other inventors outside the team) can draw on such knowledge resources as a basis for more impactful innovations (Yang et al., 2021). A similar logic applies to the *inventors' mobility* between organizations. If inventors move to another organizational setting for innovation, "the new knowledge available […], if used with existing knowledge and processes, can create new combinations of outputs" (Chang, 2022, p. 1221). Despite the coordination costs resulting from difficulties transferring the organization-specific human capital (i.e., routines, procedures, and interpersonal relationships) to a new environment, the access to a "new, complementary stock of technological knowledge" (Chang, 2022, p. 1221) can significantly foster the creation of high-impact innovations.

4.4 Methodology

4.4.1 Data, Measures, and Calibration

I utilize the dataset of 54,003 granted team-based clean energy patents filed with the USPTO between 1985 and 2015 introduced in section 3.4.1, with each patent representing a single and unique innovation *case*. To assess the degree to which a case represents an *impactful innovation*, I, once again, use the 5-year forward citations of each focal patent, adjusted for year and technological domain fixed effects. To define each patent's membership in the set of impactful innovations, I use a fuzzy calibration based on common definitions of high-impact innovations in the existing literature and the data distribution itself. A patent is considered a full member of the set if it falls within the top 5% (95th percentile) of adjusted forward citations (inclusion threshold), as defined and applied by, for example, Chang (2022). Patents between the 90th percentile (crossover point) and the 95th percentile are considered *highly impactful to some degree* and are assigned partial membership in the set. Patents between the 75th percentile (exclusion threshold) and the 90th percentile are viewed as *highly impactful to some degree* but rather out of the set, also receiving partial membership. Patents below the 75th percentile are deemed not particularly impactful and are thus non-members of the set.

I further leverage the publicly accessible patent data to operationalize the causal conditions (see also Table 3.1). First, for the *institutional diversity* within a team, I use the types of assignees (individual/unassigned, company, or public) associated with all inventors' prior patents to calculate a variation of *Blau's diversity index* (Blau, 1977) for each case, as suggested by Harrison and Klein (2007). This adjusted diversity index corrects for a bias that can occur when the number of observations (here: past patents) is potentially smaller than the number of categories (here: assignee types). I then apply a crisp calibration: cases where inventors have patented for only one type of assignee (institutional diversity index = 0) are considered not to exhibit institutional diversity, while cases showing any level of past assignee type diversity (institutional diversity index > 0) are considered institutionally diverse.

To measure *gender diversity*, I draw on predictions for the binary gender (male, female) of each inventor, provided by the *PatentsView* platform. These predictions are based on a multi-stage gender attribution algorithm using country-specific lists of names (Toole et al., 2020). Subsequently, I calculate each team's gender diversity using Blau's diversity index (Blau, 1977). Similarly, I calculate a team's *ethnic diversity*. However, since data on ethnic affiliation is not readily available for filed patents, I follow state-of-the-art practices (Kozlowski et al., 2022) and use a pre-trained machine learning model[37] that infers the ethnic affiliation (White, Black, Asian-Pacific, Hispanic) of each team member based on their last name, drawing on U.S. census data. Again, I use the adjusted Blau's diversity index (Harrison & Klein, 2007), as the number of team members may be smaller than the number of ethnic categories:

$$ethn\_div = 1 - \sum_i \left(\frac{n_i(n_i - 1)}{N(N-1)} \right)$$

In this, n_i represents the number of team members belonging to one of the $\boldsymbol{i}$ ethnic categories and N the total number of team members. In the calibration process, for both gender diversity as well as ethnic diversity, I use a fuzzy calibration with a full-exclusion threshold of just above zero (no diversity at all). Furthermore, based on the data distribution, for gender diversity, I set the crossover point to 0.25 and the full inclusion threshold to 0.4. For ethnic diversity, the crossover is set to 0.25 and the inclusion threshold to 0.75.

To measure the *dissimilarity of knowledge* held by the inventors on a team, it is common practice to use the distinct technology (sub)classes of past patents filed by each team member (e.g., Melero & Palomeras, 2015; Singh & Fleming, 2010). Building on this approach – but instead of relying on patent subclass data – I leverage the specific vector representations of each patent an inventor has filed prior to, and including, the focal patent. I compute a centroid vector from the patents' *embedding vectors*[38] as a unique knowledge vector for each inventor and calculate the

[37] I use the *ethnicolr* Python module (https://github.com/appeler/ethnicolr).
[38] Embedding vectors are obtained from the *Google Patents Research Database*.

individual distances between the knowledge vectors of all inventors on the focal patent. By adapting Blau's diversity index, I define a measure for knowledge dissimilarity that increases with the number of inventors holding distinct knowledge and reaches a maximum when the knowledge vectors of all inventors are as dissimilar as possible (see also Ferrucci & Lissoni, 2019):

$$know\_dis = \sum_{i}^{n} \left(\frac{d_i}{n}\right)^{\frac{1}{2}}$$

Here, d_i refers to the normalized cosine distance (0 for identical vectors, 1 for maximally dissimilar vectors) between the centroid knowledge vectors of two team members, and n describes the total number of distance pairs. Since there are no existing standards to build on for the calibration of this novel knowledge dissimilarity measure, I, again, turn to the data distribution itself. As existing empirical studies suggest a curvilinear relationship with the outcome (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020), I use a fuzzy bell-shaped calibration curve. Cases exhibiting moderate knowledge dissimilarity between the 33rd and 66th percentile are fully included in the set, while cases with little knowledge dissimilarity below the 10th percentile and high knowledge dissimilarity above the 90th percentile are fully excluded. The two crossover points are set at the 25th and 75th percentiles.

The measure for *recombination novelty* within a case follows the approach by Marino and Quatraro (2022) and builds on the CPC subgroup-level codes assigned to the focal patent and the team members' past patents. For each inventor, I determine all pairwise combinations of previously assigned codes and compare them with all code pairs for the focal case. I then calculate the average proportion of novel combinations represented in the focal case across all inventors, ranging from 0 (only familiar combinations) to 1 (only novel combinations). For the fuzzy calibration, I use an inclusion threshold of 0.75 (mainly novel combinations – exploration), a crossover point at 0.5, and an exclusion threshold of 0.25 (mainly familiar combinations – exploitation).

To measure *degree centrality*, I first construct collaborator networks[39] for each year within the sample period, based on all inventors listed on the granted clean energy patents filed up to and including the previous year. I then calculate each inventor's degree centrality based on collaborative ties with other inventors from past patent co-filings, using the respective year-specific network. For each case, I take the average degree centrality among the team members, normalized by the total network size, as an aggregate team-level measure. In the calibration process, I use fuzzy sets: cases where inventors have no existing collaborative ties (average degree centrality = 0) are excluded, cases above the 75th percentile are included, and the crossover point is set at the 50th percentile.

Finally, to calculate *inventor mobility*, I compile a full list of organizations with which each inventor has innovated (i.e., patent assignees), including past successful patent filings and the focal patent. I then determine the average number of unique assignees across all team members as a measure of the inventors' organizational mobility. Again, I use a fuzzy calibration based on the data distribution, with an exclusion threshold at the 25th percentile, a crossover point at the 50th percentile, and an inclusion threshold at the 75th percentile. Table 4.1 presents a statistical description of the calibrated sample.

4.4.2 Set-Theoretic Analysis (QCA)

I apply a set-theoretic analysis – more specifically QCA (Fiss, 2011; Ragin, 2000, 2008) – to explore which configurations of team composition factors (i.e., causal conditions) are associated with impactful innovations in the clean energy sector. I seek to uncover any conditions and combinations thereof that are necessary as well as those that are sufficient for achieving impactful outcomes. For both the necessity and the sufficiency analysis, I use the QCA *R* Package (Dușa, 2019). To address potential causal asymmetry, I additionally perform the same analysis for non-impactful innovations as the inverted outcome. Furthermore, impactful innovations are per definition (here: top 5% in forward citations) a *rare* outcome. As QCA relies on comparing combinations of conditions across

[39] I use the *networkx* Python module (https://networkx.org/).

cases with positive and negative outcomes to clearly distinguish configurations associated with impactful innovations from those that are not, I apply two additional steps to the construction of the sample used for the analysis. First, to effectively capture the differences between cases that are clearly impactful and those that are not, I increase contrast by only considering full members and full non-members in the outcome set, leaving out the *somewhat impactful* cases between the exclusion and inclusion thresholds. Secondly, I build on an approach recently proposed by Miric and Fiss (under review) who construct a balanced sample (i.e., equal numbers of positive and negative outcome cases) by oversampling on the positive outcome. Hence, in addition to the 3,025 cases of impactful innovations, I select another 3,025 cases, preferentially from the same domain and year, that do not represent a case of impactful innovation.

Table 4.1: Descriptive statistics for the calibrated outcome and conditions.

	mean	std	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) IMPACT_INNO	0.50	0.50									
(2) INST	0.46	0.50	0.09*								
(3) ETHN	0.37	0.45	0.00	0.01							
(4) GEND	0.25	0.42	-0.03*	0.01	0.10*						
(5) KNOW_DIS	0.48	0.40	-0.01	0.20*	0.20*	0.14*					
(6) RECOMB	0.78	0.40	-0.08*	-0.13*	-0.03*	0.03*	0.11*				
(7) DEG	0.47	0.45	-0.01	0.14*	0.11*	0.03*	0.09*	-0.31*			
(8) MOB	0.47	0.44	-0.02	0.31*	0.11*	-0.02	0.27*	-0.16*	0.24*		
(9) DOM†	0.06	0.24	0.06*	-0.01	-0.02	-0.05*	-0.01	-0.07*	-0.02	-0.03*	
(10) PRICOL†	0.42	0.45	0.07*	0.19*	0.06*	-0.02	-0.12*	-0.55*	0.40*	0.24*	0.06*

Note: This table uses the abbreviations for the outcome and conditions introduced in Table 3.1. Abbreviations are used accordingly in the following sections: IMPACT_INNO (impactful innovations), INST (institutional diversity), ETHN (ethnic diversity), GEND (gender diversity), KNOW_DIS (knowledge dissimilarity), RECOMB (recombination novelty), DEG (degree centrality / central network position), MOB (inventor mobility), DOM (domain experience), PRICOL (prior collaboration). The conditions marked with a (†) are introduced in section 4.5.4. Statistical significance for pairwise correlations ($p < 0.05$) is marked with an asterisk (*).

For the sufficiency analysis based on the resulting balanced sample of 6,050 cases, I create a truth table with each case assigned to a specific row that represents one of the $2^7 = 128$ possible combinations of causal conditions. As both cases with and without membership in the outcome set of impactful innovations can exhibit the same combination of conditions and would thus be assigned to the same row of the truth table, a consistency score is calculated for each row as a measure of "the degree to which the cases sharing a given combination of conditions […] agree in displaying the outcome in question" (Ragin, 2008, p. 44). Besides this raw *consistency*, the so-called *proportional reduction in inconsistency (PRI)* is used as additional probabilistic criterion that measures the consistency after eliminating cases that appear among combinations of conditions that are associated with both the presence as well as the absence of the observed outcome (Leppänen et al., 2023). This resolves simultaneous subset relations in which a condition or a combination of conditions appears to be sufficient for, in this study context, the creation of impactful and non-impactful innovations – a logical contradiction. I apply a raw consistency cutoff of 0.75 (Ragin, 2008) and a PRI cutoff of 0.7 (Greckhamer et al., 2018)[40]. Only truth table rows above these thresholds will be considered sufficient for yielding (non-)impactful innovations. Furthermore, to avoid including configurations in the solution that originate from only a few cases in the sample, and thus have little representative value, I use a minimum number of 30 cases (i.e., a 0.5% frequency cutoff) for a row to be considered in the algorithmic reduction of the truth table. Additionally, to add robustness to this approach, I calculate mean values and confidence intervals for raw consistency and PRI based on repeated sampling (here: 50 samples; the baseline sample plus 49 additional balanced samples using the same sampling strategy) for each row in the truth table (see also Miric & Fiss, under review). The lower bounds of the resulting 90% confidence intervals serve as conservative cutoff values.

For the necessity analysis, I choose a minimum consistency of 0.9 (Ragin, 2008). In the context of necessity analyses, consistency refers to the degree to which the set of cases where the outcome occurs is included in the set of cases with a presence or absence of any of the (combinations of) causal conditions (Duşa, 2019). However, when a condition is necessary for an outcome to be

[40] Given the crisp nature of the outcome and the structure of the calibrated data, no configurations exhibit inconsistencies by aligning simultaneously with both the presence and absence of the outcome in any of the analyses presented in the following sections. As a result, PRI scores are identical to consistency scores, and the PRI cutoff remains effectively unused. Nonetheless, for the sake of completeness, I report both PRI and consistency scores.

observed, it does not necessarily mean that condition is also relevant (i.e., a trivial necessary condition). If a certain compositional factor is found to be necessary for impactful innovations to be created but at the same time can also be observed for teams that do not create particularly impactful innovations, that condition would lack relevance. To account for this, I use a *Relevance of Necessity (RoN)* threshold of 0.7 as a second criterion for a condition to be considered both necessary and relevant.

4.5 Findings

4.5.1 Necessity Analysis

The necessity analysis reveals that no single condition or combination of conditions meets the thresholds to be considered necessary for producing impactful innovations. Hence, the necessity analysis also provides no implications for addressing specific counterfactuals, namely those containing the negation of any necessary condition (Duşa, 2019), in the subsequent sufficiency analysis. This result is not unexpected, as "necessary conditions are rare in social phenomena" (Muñoz et al., 2022, p. 309). As highlighted by Gupta et al. (2020, p. 1883), that lack of evidence for necessary conditions "reinforces the expectation of complex causality" and, thus, confirms the selection of a configurational research approach.

4.5.2 Sufficiency Analysis

Table 4.5 presents an excerpt (see Appendix 4.1.1 for the full truth table) from the populated truth table, applying a conservative 0.5% frequency cutoff. This cutoff includes only configurations associated with 30 or more cases for the analysis. Truth table rows with fewer cases are treated as logical remainders – or unobserved configurations – that lack the required level of empirical evidence. While all 128 rows of the truth table contain at least one case, only 70 configurations meet or exceed the frequency cutoff. Each table row displays the respective unique configuration of conditions, the number of associated cases, and shows the consistency and PRI values, including the raw values from the baseline truth table and the mean and bounds of the 90% confidence intervals calculated from repeated sampling. Configurations at or above the frequency, consistency, and PRI cutoff are marked with an asterisk.

As shown in Table 4.5, only two truth table rows pass all the thresholds:

(1) INST • ETHN • ~GEND • ~KNOW_DIS • ~RECOMB • ~DEG • ~MOB ⇒ IMPACT_INNO[41]
(2) INST • ETHN • ~GEND • ~KNOW_DIS • ~RECOMB • ~DEG • MOB ⇒ IMPACT_INNO

These two rows only differ in a single condition – *inventor mobility*. Since both the presence and the absence of mobile inventors are associated with impactful innovations while all other conditions remain identical, this expression can also be represented as

INST • ETHN • ~GEND • ~KNOW_DIS • ~RECOMB • ~DEG • (~MOB + MOB) ⇒ IMPACT_INNO

and, thus, be reduced to

INST • ETHN • ~GEND • ~KNOW_DIS • ~RECOMB • ~DEG ⇒ IMPACT_INNO

using Boolean algebra. Therefore, inventor mobility becomes a "don't care" condition that may or may not be present in that configuration for impactful innovations to be the observed outcome. This kind of logical reduction is typically performed during truth table minimization until no further simplification is possible. However, additional simplification can be achieved by considering logical remainders that have few or no empirical instances. Depending on the types of remainders included, different solutions emerge. For example, when using *easy counterfactuals* for further simplification, theoretical knowledge is leveraged to specify directional expectations about a condition. Even if a configuration lacks empirical instances, if the presence or absence of an outcome is theoretically expected to cause the outcome, this information can be used to add "a redundant causal condition […] to a set of causal conditions that by themselves already lead to the outcome in question" (Fiss, 2011, p. 403), resulting in a more parsimonious intermediate solution. In accordance with insights from past empirical studies, I specify that the presence of institutional diversity, a central network

[41] Meaning of symbols in logical expressions: (•) – logical AND conjunction; (+) – logical OR conjunction; (~) – negation

position (i.e., high degree centrality), and moderate knowledge dissimilarity are associated with impactful innovations. I do not specify directional expectations for the other conditions due to the relatively weak empirical basis and the abductive nature of this study. In a subsequent step, I allow all remainders[42] to be used for further logical minimization, including the use of *difficult counterfactuals* that are not supported by substantive knowledge. This involves making stronger assumptions about the expected outcome for configurations lacking empirical evidence and, thus, whether these configurations can be used for logical simplification.

Table 4.2 shows the configuration chart resulting from the Boolean minimization. Full circles indicate the presence of a condition in a configuration, while crossed circles denote their absence. Empty fields indicate that a condition is irrelevant for a particular configuration – both its presence and absence, in conjunction with the other conditions, are associated with the observed outcome. The larger circles represent the causal core (Fiss, 2011) that appears not only in the solution with simplifying assumptions based on directional expectations but also in the most parsimonious solution where all remainders are used for potential simplification. The smaller circles illustrate the causal periphery, which is not part of the most parsimonious solution.

The truth table minimization yields only a single, fairly complex team configuration (1a), suggesting a very narrow path that consistently leads to an impactful innovation outcome. I therefore extend the analysis beyond the more common configuration(s) to also include rarer configurations that are associated with impactful innovation, even though they are less frequently observed (i.e., lowering the frequency cutoff). Thus, in Table 4.2, I further show the configurations resulting from the truth table minimization (see Table 4.6 for an excerpt and Appendix 4.1.1 for the full truth table) when including all configurations with at least two empirical instances. Since this more liberal

[42] After verifying the absence of contradictory simplifying assumptions and ensuring that no untenable remainders result from potential necessary conditions.

frequency cutoff leaves very few remainders for further simplification, I do not distinguish between core and peripheral conditions for these rare configurations (1b and 2).

Table 4.2: Configuration chart for impactful innovations with initial model specification.

	Common Configurations	**Including Rare Configurations**	
	(1a)	(1b)	(2)
Institutional Diversity	⬤	●	⊗
Ethnic Diversity	⊗	⊗	●
Gender Diversity	⊗	⊗	●
Moderate Knowledge Dissimilarity (∩)	⨂	⊗	
Novel Recombination	⨂	⊗	⊗
Central Network Position	⨂	⊗	⊗
Mobile Inventors			●
Consistency	0.80	0.80	0.87
Raw Coverage	0.024	0.024	0.004
Unique Coverage	0.024	0.024	0.004
Overall Model Consistency	**0.80**	**0.81**	
Overall Model Coverage	**0.024**	**0.029**	

Note: Knowledge dissimilarity has a bell-shaped calibration curve. Thus, the presence of this condition indicates moderate levels of knowledge dissimilarity, and absence can be linked to either low or high knowledge dissimilarity.

The more common configuration (1a) suggests that impactful innovation outcomes are linked to teams composed of inventors that have innovated in diverse institutional settings in the past, use combinations of knowledge components they are already familiar with from previous innovation projects, and with few ties from past collaborations to inventors outside the team. Additionally, though less pronounced, such teams also tend to be demographically homogeneous. Interestingly, the configuration also includes the absence of moderate knowledge dissimilarity as a core condition. While prior empirical studies suggest an inverted U-shaped relationship between knowledge dissimilarity among team members and the impact of an innovation – which was considered in the bell-shaped calibration curve for this condition – the results indicate that either particularly low or particularly high levels of knowledge dissimilarity are key components in this recipe for impactful innovations. Configuration (1a) remains essentially unchanged after lowering the frequency cutoff (1b). However, including rarer configurations reveals another distinct, complex, and narrow pathway to impactful innovations: configuration (2) is characterized by inventors who continuously innovate for the same type of institution, but frequently moved between organizations. These teams also exhibit higher demographic diversity and a high familiarity with the combination of knowledge components used for the focal innovation. Interestingly, although team members have innovated for a larger number of organizations in the past, these teams display few external ties based on past collaborations.

Although the analysis reveals consistent team configurations associated with impactful innovations, the models explain only a relatively small fraction of the cases that yielded such outcomes. Moreover, there is no explanatory overlap between the configurations, with unique coverage matching the raw coverage values. This suggests that configurations (1a+b) and (2) capture mutually independent causal pathways.

4.5.3 Revisiting Knowledge Diversity: Insights from Recalibration

Insights from past empirical studies on the (isolated) role of knowledge dissimilarity in creating particularly impactful innovations suggest that moderate levels of dissimilarity among team members are most beneficial. While some dissimilarity has shown to enhance innovation impact by enabling novel, complementary knowledge combinations, excessive dissimilarity hinders this effect due to integration challenges, increased coordination costs, and communication barriers, leading to an inverted U-shaped relationship (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020). However, the pathways to impactful innovations that emerged from the sufficiency analysis in the previous section largely included the absence of moderate knowledge dissimilarity as a core condition, which can be linked to both high and low levels of knowledge dissimilarity. To better understand the role of knowledge dissimilarity, I conduct an additional analysis after recalibrating the knowledge dissimilarity condition (Table 4.3).

More specifically, instead of a bell-shaped calibration curve, I use the same calibration approach as for the other conditions, with a fuzzy logistic calibration that assigns set membership to high values of knowledge dissimilarity (above the 75th percentile) and non-membership to low values (below the 25th percentile), and with the crossover point at the 50th percentile.

Table 4.3: Configuration chart for impactful innovations with recalibrated knowledge dissimilarity condition.

	Common Configurations	**Including Rare Configurations**	
	(1a)	(1b)	(2)
Institutional Diversity	●	●	⊗
Ethnic Diversity	⊗	⊗	●
Gender Diversity	⊗	⊗	●
Knowledge Dissimilarity (ʃ)	⊗	⊗	⊗
Novel Recombination	⊗	⊗	⊗
Central Network Position	⊗	⊗	⊗
Mobile Inventors			●
Consistency	0.76	0.76	0.80
Raw Coverage	0.032	0.032	0.002
Unique Coverage	0.032	0.032	0.002
Overall Model Consistency	**0.76**	**0.76**	
Overall Model Coverage	**0.032**	**0.034**	

Note: Knowledge dissimilarity now has a logistic calibration curve. Thus, the presence of this condition indicates high levels, and absence indicates low levels of knowledge dissimilarity.

Once again, I find no necessary conditions that pass the respective thresholds. For the sufficiency analysis, I use the same baseline sample along with the 49 additional samples to calculate the confidence intervals for consistency and PRI. I apply the same frequency cutoffs as before: 0.5% for a conservative analysis and at least two cases for a more liberal analysis that includes rarer configurations. I present excerpts from the truth tables in Table 4.7 and Table 4.8, with the full truth tables provided in Appendix 4.1.2. As indicated in the truth tables, I accepted a slightly lower consistency threshold of 0.74. All other parameters and the directional expectations for institutional diversity and the central network position remain unchanged. However, this time, I do not specify any assumptions for knowledge dissimilarity to arrive at an intermediate solution. For the analysis based on the conservative frequency cutoff, I, again, use the remainders to calculate a parsimonious solution to distinguish core from peripheral conditions.

The emerging configurations remain largely the same. However, it becomes apparent that low levels of knowledge dissimilarity, rather than high dissimilarity, are associated with the revealed pathways to impactful innovations, although – after recalibration – the absence of knowledge dissimilarity no longer emerges as a core condition.

4.5.4 Supplemental Analysis with Contrasting Conditions

The configurational analyses in the previous sections revealed two narrow pathways to impactful innovations, describing – among other characteristics – teams that are already familiar with combining the knowledge components used (i.e., absence of novel recombination) and have limited ties to outside inventors through prior collaborations (i.e., absence of a central network position). In causally complex phenomena viewed through a configurational lens, causal asymmetry implies that the absence of certain conditions being associated with an outcome does not necessarily mean that their presence leads to the absence of the outcome. However, if the absence of some conditions is associated with impactful innovations, it is worthwhile to explore whether the presence of contrasting conditions might likewise contribute to impactful innovations. More specifically, the observation that teams that do not explore *novel* knowledge combinations and have few *external* ties tend to produce impactful innovations suggests that teams with *experience* in the innovation area and a cohesive *internal* network might represent a pathway to impactful innovations. Past studies have shown that *domain experience* enables teams to effectively select and recombine distinct knowledge through a deep understanding of the field (Li et al., 2018; Schillebeeckx et al., 2019; Wang et al., 2017). Moreover, *prior collaboration* with the same collaborators has been found to foster impactful innovation by enhancing coordination capabilities and communication skills, enabling teams to develop effective routines that help integrate knowledge, especially when the inventors' knowledge bases are dissimilar (Jiao et al., 2022).

Therefore, I perform an additional analysis in which I substitute recombination novelty with domain experience and replace the central network position with prior collaboration among team members[43]. Through this supplemental analysis, I aim to deepen the understanding of the mechanisms by which familiarity with the innovation area and the dynamics of internal versus external ties contribute to impactful innovations. Moreover, by examining these contrasting conditions, I seek to verify if their presence supports and reinforces the findings of the original configurations uncovered earlier.

I measure prior collaboration as the number of prior pairwise collaborations among any two inventors normalized by the number of possible inventor pairs. Cases are fully excluded from the set of teams with prior collaboration if none of the inventors has co-invented with any of the other inventors in the past. Cases are fully included if inventors have collaborated already twice on average. A single prior collaboration on average sets the crossover point for the calibration. To measure domain experience, I use the number of patents successfully filed by any team member that was assigned to one of the CPC subgroups assigned to the focal patent. Due to the vast majority of cases exhibiting no previous domain experience at all, I use a crisp calibration and assign set membership to cases in which some domain experience exists.

After substituting the two conditions, I still do not find any necessary conditions or combinations thereof. Since there is no solid theoretical foundation to confidently define directional expectations for the newly added conditions, I retain only the directional expectation specified for institutional diversity. For the rarer configurations, due to the significantly larger number of

[43] In the cluster analysis presented in Chapter 3, prior collaboration emerges close to the central cluster of conditions, while domain experience plays a key role in the best-performing models specified with only 4 causal conditions (see also Appendix 3.2).

combinations passing the consistency and PRI thresholds, I increase the frequency cutoff from at least two to five cases. All other parameters remain the same. Based on the truth table including rare configurations, I identify and exclude two contradictory simplifying assumptions that – if not excluded from the remainders used for minimization – would paradoxically contribute to more parsimonious explanations for both the outcome and its negation (Duşa, 2019). Excerpts from the respective truth tables are presented in Table 4.9 and Table 4.10, and the full truth tables in Appendix 4.1.3. Table 4.4 shows the resulting configuration chart.

Table 4.4: Configuration chart for impactful innovations with substituted conditions.

	Common Configurations	**Including Rare Configurations**			
	(1a)	(1b)	(2)	(3)	(4)
Institutional Diversity	●	●	●	⊗	●
Ethnic Diversity	⊗	⊗	⊗	●	●
Gender Diversity	⊗	⊗	⊗		●
Knowledge Dissimilarity (∫)	⊗	⊗	●	●	⊗
Domain Experience	⬤	●	●	●	⊗
Prior Collaboration	●	●	●	●	●
Mobile Inventors	●	●	⊗	●	⊗
Consistency	0.79	0.79	0.81	0.91	0.83
Raw Coverage	0.008	0.008	0.003	0.007	0.009
Unique Coverage	0.008	0.008	0.003	0.007	0.009
Overall Model Consistency	**0.79**	**0.84**			
Overall Model Coverage	**0.008**	**0.027**			

Note: Knowledge dissimilarity, once again, has a logistic calibration curve. Thus, the presence of this condition indicates high levels, and absence indicates low levels of knowledge dissimilarity.

The configurations with the substituted conditions confirm that domain experience and prior collaboration among inventors are critical building blocks for teams that produce impactful innovation outcomes. Configuration (1a) highlights a more common pathway, with domain experience standing out as a single core condition. Across all identified pathways, including the rarer configurations, domain experience is present in all but one configuration (4). The presence of prior collaboration appears even more consistently, being part of every configuration. Interestingly, some configurations include the presence of relatively dissimilar knowledge among team members when domain experience and prior collaboration are present. In summary, this additional analysis reinforces the results from the previous analyses and supports the idea that, rather than relying on novel recombination of knowledge and drawing on external inputs and resources from outside ties, teams achieve particularly impactful innovations by leveraging their existing domain expertise and forming strong ties with their team members over multiple innovation projects.

4.5.5 Analysis for Non-Impactful Innovations

I follow common practices (Fiss, 2011; Greckhamer, 2016; Gupta et al., 2020) and perform an additional analysis on the absence of the outcome (i.e., non-impactful innovations) to investigate potential team configurations that explicitly hinder the creation of particularly impactful innovations and to shed light on potential causally asymmetric effects. I conduct the analysis for non-impactful innovations with the initial bell-shaped calibration of the knowledge dissimilarity condition (see section 4.5.2) as well as for the alternate calibration (see section 4.5.3) and the two substituted conditions (see section 4.5.4). The analysis does not unveil any necessary conditions for any of the model specifications. The sufficiency analysis results in only one consistent truth table row with the two substituted conditions and only for the lower frequency cutoff including configurations with five or more cases (Appendix 4.4). Teams exhibiting this configuration are characterized by the absence of institutional diversity, demographic diversity (i.e., ethnicity and gender), knowledge dissimilarity, prior collaboration, and inventor mobility, as well as by the presence of domain experience. This underscores the significance of past project experience as a team but, at the same time, shows that domain experience – while representing a core building block for the creation of impactful innovations – does not guarantee for avoiding non-impactful outcomes.

Table 4.5: Truth table (excerpt) for configurations associated with **impactful innovations**; **initial model specification** for moderate knowledge dissimilarity (bell-shaped calibration); including more common configurations with **frequency cutoff: 0.5 % (30 cases).**

	Conditions								Consistency			PRI			
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	1	0	0	0	0	0	0	41	0.80	0.79	[0.78,0.80]	0.80	0.79	[0.78,0.80]	*
(2)	1	0	0	0	0	0	1	48	0.79	0.79	[0.78,0.80]	0.79	0.79	[0.78,0.80]	*
(3)	1	1	1	0	1	0	0	34	0.70	0.69	[0.68,0.70]	0.70	0.69	[0.68,0.70]	
(4)	1	0	0	0	0	1	0	60	0.68	0.70	[0.69,0.71]	0.68	0.70	[0.69,0.71]	
(5)	1	1	0	0	1	0	0	41	0.68	0.62	[0.62,0.63]	0.68	0.62	[0.62,0.63]	
(6)	1	0	0	0	1	1	0	55	0.66	0.66	[0.66,0.67]	0.66	0.66	[0.66,0.67]	
(7)	1	1	1	0	1	0	1	44	0.65	0.60	[0.60,0.61]	0.65	0.60	[0.60,0.61]	
(8)	1	0	0	1	0	1	1	103	0.64	0.62	[0.62,0.63]	0.64	0.62	[0.62,0.63]	
(9)	0	1	0	1	0	1	1	72	0.63	0.63	[0.62,0.63]	0.63	0.63	[0.62,0.63]	
(10)	1	0	0	1	0	1	0	35	0.62	0.63	[0.63,0.64]	0.62	0.63	[0.63,0.64]	
(11)	1	1	0	0	1	1	0	32	0.61	0.62	[0.61,0.63]	0.61	0.62	[0.61,0.63]	
(12)	1	0	0	1	0	0	1	35	0.61	0.65	[0.64,0.66]	0.61	0.65	[0.64,0.66]	
(13)	1	0	0	0	1	0	1	128	0.60	0.59	[0.59,0.60]	0.60	0.59	[0.59,0.60]	
(14)	1	0	0	0	1	0	0	105	0.60	0.62	[0.62,0.63]	0.60	0.62	[0.62,0.63]	
(15)	1	1	0	0	0	1	1	77	0.59	0.56	[0.55,0.57]	0.59	0.56	[0.55,0.57]	
(16)	1	1	1	1	1	0	0	34	0.58	0.63	[0.62,0.64]	0.58	0.63	[0.62,0.64]	
(17)	1	0	0	1	1	1	0	76	0.57	0.61	[0.60,0.62]	0.57	0.61	[0.60,0.62]	
(18)	1	1	1	1	1	1	1	40	0.57	0.61	[0.60,0.62]	0.57	0.61	[0.60,0.62]	
(19)	1	1	0	1	1	0	0	51	0.56	0.54	[0.53,0.55]	0.56	0.54	[0.53,0.55]	
(20)	1	0	1	1	1	1	1	36	0.55	0.55	[0.54,0.56]	0.55	0.55	[0.54,0.56]	
(21)	1	0	0	0	0	1	1	74	0.55	0.54	[0.54,0.55]	0.55	0.54	[0.54,0.55]	
(22)	1	1	0	0	1	0	1	95	0.54	0.53	[0.52,0.53]	0.54	0.53	[0.52,0.53]	
(23)	1	0	0	1	1	0	0	135	0.54	0.53	[0.53,0.54]	0.54	0.53	[0.53,0.54]	
(24)	0	0	0	0	0	0	0	52	0.54	0.54	[0.54,0.55]	0.54	0.54	[0.54,0.55]	
(25)	0	1	0	0	1	0	0	156	0.54	0.51	[0.50,0.51]	0.54	0.51	[0.50,0.51]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.1 for the full table.

Table 4.6: Truth table (excerpt) for configurations associated with **impactful innovations**; **initial model specification** for moderate knowledge dissimilarity (bell-shaped calibration); including rare configurations with **frequency cutoff: 2 cases.**

	Conditions								Consistency			PRI			
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	0	1	1	1	0	0	1	6	0.89	0.84	[0.82,0.85]	0.89	0.84	[0.82,0.85]	*
(2)	0	1	1	0	0	0	1	2	0.83	0.84	[0.82,0.85]	0.83	0.84	[0.82,0.85]	*
(3)	1	0	1	0	0	0	0	2	0.82	0.55	[0.53,0.58]	0.82	0.55	[0.53,0.58]	
(4)	1	0	0	0	0	0	0	41	0.80	0.79	[0.78,0.80]	0.80	0.79	[0.78,0.80]	*
(5)	1	0	1	0	0	1	0	17	0.79	0.73	[0.71,0.74]	0.79	0.73	[0.71,0.74]	
(6)	1	0	0	0	0	0	1	48	0.79	0.79	[0.78,0.80]	0.79	0.79	[0.78,0.80]	*
(7)	0	1	0	1	0	0	1	5	0.78	0.66	[0.65,0.67]	0.78	0.66	[0.65,0.67]	
(8)	0	1	0	0	0	0	1	18	0.76	0.74	[0.73,0.76]	0.76	0.74	[0.73,0.76]	
(9)	1	1	1	0	0	0	0	3	0.74	0.73	[0.71,0.75]	0.74	0.73	[0.71,0.75]	
(10)	1	1	0	0	0	1	0	20	0.74	0.65	[0.64,0.67]	0.74	0.65	[0.64,0.67]	
(11)	1	1	1	1	0	1	0	10	0.72	0.65	[0.64,0.67]	0.72	0.65	[0.64,0.67]	
(12)	0	0	1	1	0	1	1	14	0.71	0.64	[0.62,0.65]	0.71	0.64	[0.62,0.65]	
(13)	1	1	1	0	1	0	0	34	0.70	0.69	[0.68,0.70]	0.70	0.69	[0.68,0.70]	
(14)	1	0	0	0	0	1	0	60	0.68	0.70	[0.69,0.71]	0.68	0.70	[0.69,0.71]	
(15)	1	1	0	0	1	0	0	41	0.68	0.62	[0.62,0.63]	0.68	0.62	[0.62,0.63]	
(16)	0	0	0	1	0	0	1	19	0.67	0.66	[0.65,0.67]	0.67	0.66	[0.65,0.67]	
(17)	1	1	1	0	0	1	0	14	0.66	0.64	[0.63,0.66]	0.66	0.64	[0.63,0.66]	
(18)	0	1	0	0	0	0	0	13	0.66	0.61	[0.59,0.62]	0.66	0.61	[0.59,0.62]	
(19)	1	0	0	0	1	1	0	55	0.66	0.66	[0.66,0.67]	0.66	0.66	[0.66,0.67]	
(20)	1	1	1	0	1	0	1	44	0.65	0.60	[0.60,0.61]	0.65	0.60	[0.60,0.61]	
(21)	0	0	1	1	0	0	1	4	0.65	0.62	[0.60,0.64]	0.65	0.62	[0.60,0.64]	
(22)	1	0	0	1	0	1	1	103	0.64	0.62	[0.62,0.63]	0.64	0.62	[0.62,0.63]	
(23)	1	1	0	0	0	0	0	2	0.64	0.55	[0.53,0.58]	0.64	0.55	[0.53,0.58]	
(24)	1	0	1	0	1	1	0	21	0.63	0.58	[0.57,0.59]	0.63	0.58	[0.57,0.59]	
(25)	1	0	0	1	0	0	0	11	0.63	0.61	[0.60,0.62]	0.63	0.61	[0.60,0.62]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.1 for the full table.

Table 4.7: Truth table (excerpt) for configurations associated with **impactful innovations**; model specification with **recalibrated knowledge dissimilarity** condition; including more common configurations with **frequency cutoff: 0.5 % (30 cases).**

	Conditions								**Consistency**			**PRI**			
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	1	0	0	0	0	0	0	49	0.76	0.75	[0.75,0.76]	0.76	0.75	[0.75,0.76]	*
(2)	1	0	0	0	0	0	1	67	0.73	0.75	[0.74,0.75]	0.73	0.75	[0.74,0.75]	*
(3)	1	0	0	0	0	1	0	55	0.69	0.67	[0.66,0.67]	0.69	0.67	[0.66,0.67]	
(4)	1	1	0	1	1	0	0	63	0.64	0.60	[0.59,0.61]	0.64	0.60	[0.59,0.61]	
(5)	1	1	1	1	1	0	1	63	0.63	0.60	[0.59,0.61]	0.63	0.60	[0.59,0.61]	
(6)	1	1	1	1	1	0	0	49	0.62	0.64	[0.63,0.65]	0.62	0.64	[0.63,0.65]	
(7)	1	0	0	0	0	1	1	96	0.61	0.59	[0.59,0.60]	0.61	0.59	[0.59,0.60]	
(8)	1	0	0	1	0	1	0	40	0.61	0.68	[0.67,0.69]	0.61	0.68	[0.67,0.69]	
(9)	0	1	0	0	0	1	1	57	0.60	0.63	[0.62,0.64]	0.60	0.63	[0.62,0.64]	
(10)	1	0	0	0	1	1	0	64	0.60	0.63	[0.62,0.63]	0.60	0.63	[0.62,0.63]	
(11)	1	0	0	1	0	1	1	81	0.60	0.60	[0.60,0.61]	0.60	0.60	[0.60,0.61]	
(12)	1	0	0	1	1	1	0	67	0.59	0.63	[0.63,0.64]	0.59	0.63	[0.63,0.64]	
(13)	1	1	0	1	1	1	0	35	0.58	0.58	[0.57,0.59]	0.58	0.58	[0.57,0.59]	
(14)	1	0	0	1	1	0	0	121	0.57	0.58	[0.57,0.58]	0.57	0.58	[0.57,0.58]	
(15)	1	1	0	0	0	1	1	68	0.57	0.59	[0.58,0.59]	0.57	0.59	[0.58,0.59]	
(16)	1	0	0	0	1	1	1	124	0.56	0.56	[0.55,0.56]	0.56	0.56	[0.55,0.56]	
(17)	1	0	0	1	1	0	1	169	0.55	0.55	[0.55,0.55]	0.55	0.55	[0.55,0.55]	
(18)	1	0	0	0	1	0	0	119	0.54	0.55	[0.55,0.56]	0.54	0.55	[0.55,0.56]	
(19)	0	0	0	0	0	0	0	58	0.53	0.53	[0.52,0.53]	0.53	0.53	[0.52,0.53]	
(20)	1	1	0	1	1	0	1	126	0.53	0.52	[0.51,0.52]	0.53	0.52	[0.51,0.52]	
(21)	0	0	0	0	1	1	0	148	0.53	0.50	[0.50,0.50]	0.53	0.50	[0.50,0.50]	
(22)	0	1	1	1	1	0	1	44	0.53	0.58	[0.57,0.59]	0.53	0.58	[0.57,0.59]	
(23)	1	0	0	0	1	0	1	130	0.53	0.55	[0.55,0.56]	0.53	0.55	[0.55,0.56]	
(24)	0	1	0	0	1	0	0	185	0.52	0.50	[0.50,0.50]	0.52	0.50	[0.50,0.50]	
(25)	0	1	0	1	1	0	0	128	0.52	0.53	[0.53,0.53]	0.52	0.53	[0.53,0.53]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.2 for the full table.

Table 4.8: Truth table (excerpt) for configurations associated with **impactful innovations**; model specification with **recalibrated knowledge dissimilarity** condition; including rare configurations with **frequency cutoff: 2 cases.**

	Conditions								Consistency			PRI			
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	1	1	1	0	0	0	0	2	0.83	0.74	[0.71,0.76]	0.83	0.74	[0.71,0.76]	
(2)	1	1	1	0	0	1	0	13	0.82	0.72	[0.71,0.74]	0.82	0.72	[0.71,0.74]	
(3)	0	1	0	1	0	0	1	15	0.80	0.72	[0.71,0.74]	0.80	0.72	[0.71,0.74]	
(4)	0	1	1	0	0	0	1	8	0.80	0.79	[0.77,0.80]	0.80	0.79	[0.77,0.80]	*
(5)	1	0	0	0	0	0	0	49	0.76	0.75	[0.75,0.76]	0.76	0.75	[0.75,0.76]	*
(6)	1	0	1	0	0	1	0	19	0.75	0.71	[0.70,0.72]	0.75	0.71	[0.70,0.72]	
(7)	1	0	0	0	0	0	1	67	0.73	0.75	[0.74,0.75]	0.73	0.75	[0.74,0.75]	*
(8)	1	0	0	0	0	1	0	55	0.69	0.67	[0.66,0.67]	0.69	0.67	[0.66,0.67]	
(9)	0	1	0	1	0	0	0	3	0.69	0.62	[0.60,0.63]	0.69	0.62	[0.60,0.63]	
(10)	0	0	1	1	0	0	1	4	0.69	0.65	[0.63,0.67]	0.69	0.65	[0.63,0.67]	
(11)	1	1	0	0	0	1	0	21	0.69	0.66	[0.65,0.67]	0.69	0.66	[0.65,0.67]	
(12)	0	1	0	0	0	0	1	8	0.68	0.59	[0.57,0.61]	0.68	0.59	[0.57,0.61]	
(13)	0	0	0	0	0	0	1	27	0.68	0.62	[0.61,0.63]	0.68	0.62	[0.61,0.63]	
(14)	0	1	0	0	0	0	0	16	0.68	0.61	[0.60,0.62]	0.68	0.61	[0.60,0.62]	
(15)	0	0	1	1	0	1	1	9	0.67	0.59	[0.57,0.60]	0.67	0.59	[0.57,0.60]	
(16)	1	1	1	0	1	0	0	19	0.65	0.68	[0.67,0.69]	0.65	0.68	[0.67,0.69]	
(17)	0	0	0	1	0	0	0	8	0.65	0.62	[0.61,0.63]	0.65	0.62	[0.61,0.63]	
(18)	1	1	1	1	0	1	0	11	0.64	0.64	[0.63,0.65]	0.64	0.64	[0.63,0.65]	
(19)	1	1	0	1	1	0	0	63	0.64	0.60	[0.59,0.61]	0.64	0.60	[0.59,0.61]	
(20)	1	1	1	1	1	0	1	63	0.63	0.60	[0.59,0.61]	0.63	0.60	[0.59,0.61]	
(21)	1	1	1	1	1	0	0	49	0.62	0.64	[0.63,0.65]	0.62	0.64	[0.63,0.65]	
(22)	1	0	1	1	0	0	0	2	0.62	0.49	[0.47,0.51]	0.62	0.49	[0.47,0.51]	
(23)	1	0	0	0	0	1	1	96	0.61	0.59	[0.59,0.60]	0.61	0.59	[0.59,0.60]	
(24)	1	0	1	0	1	1	0	21	0.61	0.62	[0.61,0.63]	0.61	0.62	[0.61,0.63]	
(25)	1	1	0	0	0	0	1	14	0.61	0.63	[0.62,0.65]	0.61	0.63	[0.62,0.65]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.2 for the full table.

Table 4.9: Truth table (excerpt) for configurations associated with **impactful innovations**; model specification with recalibrated knowledge dissimilarity and **substituted conditions**; including more common configurations with **frequency cutoff: 0.5 % (30 cases).**

	Conditions								**Consistency**			**PRI**			
	INST	ETHN	GEND	KNOW_DIS	DOM	PRICOL	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	1	0	0	0	1	1	1	36	0.79	0.82	[0.80,0.83]	0.79	0.82	[0.80,0.83]	*
(2)	1	0	1	0	0	1	0	44	0.72	0.69	[0.68,0.70]	0.72	0.69	[0.68,0.70]	
(3)	1	0	0	0	0	1	0	160	0.66	0.68	[0.67,0.68]	0.66	0.68	[0.67,0.68]	
(4)	1	0	0	0	0	1	1	265	0.62	0.61	[0.60,0.61]	0.62	0.61	[0.60,0.61]	
(5)	1	1	0	1	0	0	0	76	0.60	0.59	[0.58,0.59]	0.60	0.59	[0.58,0.59]	
(6)	1	1	0	1	0	1	0	32	0.60	0.55	[0.54,0.55]	0.60	0.55	[0.54,0.55]	
(7)	1	0	0	1	0	1	0	67	0.58	0.62	[0.61,0.62]	0.58	0.62	[0.61,0.62]	
(8)	1	1	1	1	0	0	0	63	0.58	0.61	[0.60,0.61]	0.58	0.61	[0.60,0.61]	
(9)	1	0	0	1	0	1	1	182	0.57	0.58	[0.57,0.58]	0.57	0.58	[0.57,0.58]	
(10)	1	1	1	1	0	0	1	80	0.57	0.55	[0.54,0.55]	0.57	0.55	[0.54,0.55]	
(11)	1	0	0	1	0	0	0	145	0.57	0.59	[0.58,0.59]	0.57	0.59	[0.58,0.59]	
(12)	1	1	0	0	0	1	1	131	0.56	0.58	[0.58,0.59]	0.56	0.58	[0.58,0.59]	
(13)	1	0	0	0	0	0	0	105	0.55	0.56	[0.56,0.57]	0.55	0.56	[0.56,0.57]	
(14)	1	1	0	0	0	1	0	48	0.55	0.58	[0.57,0.58]	0.55	0.58	[0.57,0.58]	
(15)	1	1	0	0	0	0	0	35	0.53	0.53	[0.52,0.53]	0.53	0.53	[0.52,0.53]	
(16)	0	1	1	1	0	0	0	70	0.52	0.50	[0.50,0.51]	0.52	0.50	[0.50,0.51]	
(17)	0	1	0	0	0	1	1	106	0.52	0.53	[0.52,0.53]	0.52	0.53	[0.52,0.53]	
(18)	0	1	0	1	0	1	0	52	0.52	0.49	[0.48,0.49]	0.52	0.49	[0.48,0.49]	
(19)	0	0	0	1	0	1	0	60	0.51	0.53	[0.53,0.54]	0.51	0.53	[0.53,0.54]	
(20)	1	1	1	1	0	1	1	91	0.51	0.54	[0.54,0.55]	0.51	0.54	[0.54,0.55]	
(21)	1	0	0	0	0	0	1	112	0.51	0.53	[0.53,0.54]	0.51	0.53	[0.53,0.54]	
(22)	0	1	0	1	0	0	0	158	0.50	0.51	[0.51,0.51]	0.50	0.51	[0.51,0.51]	
(23)	0	0	1	0	0	1	1	35	0.50	0.47	[0.46,0.47]	0.50	0.47	[0.46,0.47]	
(24)	0	0	0	1	0	0	0	188	0.50	0.49	[0.48,0.49]	0.50	0.49	[0.48,0.49]	
(25)	1	0	1	0	0	1	1	40	0.50	0.54	[0.53,0.55]	0.50	0.54	[0.53,0.55]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.3 for the full table.

Table 4.10: Truth table (excerpt) for configurations associated with **impactful innovations**; model specification with recalibrated knowledge dissimilarity and **substituted conditions**; including rare configurations with **frequency cutoff: 5 cases.**

	Conditions								Consistency			PRI			
	INST	ETHN	GEND	KNOW_DIS	DOM	PRICOL	MOB	N	raw	mean	90% CI	raw	mean	90% CI	
(1)	0	1	0	1	1	1	1	21	0.92	0.87	[0.85,0.88]	0.92	0.87	[0.85,0.88]	*
(2)	0	1	1	1	1	1	1	5	0.89	0.93	[0.91,0.94]	0.89	0.93	[0.91,0.94]	*
(3)	0	1	0	0	1	1	0	11	0.84	0.76	[0.74,0.78]	0.84	0.76	[0.74,0.78]	
(4)	1	1	1	0	0	1	0	27	0.83	0.77	[0.76,0.78]	0.83	0.77	[0.76,0.78]	*
(5)	1	0	0	1	1	1	0	9	0.81	0.80	[0.79,0.82]	0.81	0.80	[0.79,0.82]	*
(6)	1	0	0	0	1	1	1	36	0.79	0.82	[0.80,0.83]	0.79	0.82	[0.80,0.83]	*
(7)	1	1	0	1	1	0	1	12	0.75	0.76	[0.74,0.78]	0.75	0.76	[0.74,0.78]	
(8)	0	0	0	1	1	1	0	6	0.74	0.75	[0.73,0.76]	0.74	0.75	[0.73,0.76]	
(9)	1	0	1	0	0	1	0	44	0.72	0.69	[0.68,0.70]	0.72	0.69	[0.68,0.70]	
(10)	0	0	0	0	1	1	1	15	0.70	0.75	[0.74,0.77]	0.70	0.75	[0.74,0.77]	
(11)	1	0	0	0	1	1	0	16	0.69	0.71	[0.70,0.72]	0.69	0.71	[0.70,0.72]	
(12)	1	0	0	1	1	1	1	17	0.69	0.71	[0.69,0.73]	0.69	0.71	[0.69,0.73]	
(13)	1	0	0	0	0	1	0	160	0.66	0.68	[0.67,0.68]	0.66	0.68	[0.67,0.68]	
(14)	0	0	0	0	1	1	0	26	0.66	0.58	[0.57,0.59]	0.66	0.58	[0.57,0.59]	
(15)	1	0	0	1	1	0	1	6	0.65	0.63	[0.62,0.65]	0.65	0.63	[0.62,0.65]	
(16)	1	1	1	1	0	1	0	24	0.63	0.63	[0.62,0.64]	0.63	0.63	[0.62,0.64]	
(17)	1	0	0	0	0	1	1	265	0.62	0.61	[0.60,0.61]	0.62	0.61	[0.60,0.61]	
(18)	0	1	0	1	1	1	0	13	0.60	0.72	[0.70,0.74]	0.60	0.72	[0.70,0.74]	
(19)	1	1	0	1	0	0	0	76	0.60	0.59	[0.58,0.59]	0.60	0.59	[0.58,0.59]	
(20)	1	1	0	1	0	1	0	32	0.60	0.55	[0.54,0.55]	0.60	0.55	[0.54,0.55]	
(21)	1	0	0	0	1	0	0	7	0.60	0.61	[0.59,0.63]	0.60	0.61	[0.59,0.63]	
(22)	1	0	0	1	1	0	0	10	0.59	0.60	[0.58,0.61]	0.59	0.60	[0.58,0.61]	
(23)	1	0	0	1	0	1	0	67	0.58	0.62	[0.61,0.62]	0.58	0.62	[0.61,0.62]	
(24)	1	1	1	1	0	0	0	63	0.58	0.61	[0.60,0.61]	0.58	0.61	[0.60,0.61]	
(25)	0	1	0	1	1	0	1	5	0.58	0.69	[0.65,0.73]	0.58	0.69	[0.65,0.73]	
...															

Note: This table excerpt is sorted by raw consistency and does not show rows below the frequency cutoff (counterfactuals). See Appendix 4.1.3 for the full table.

4.5.6 Robustness Tests

Building on common practices for assessing robustness of findings from large-N QCA (Greckhamer et al., 2018; Leppänen et al., 2023; Rutten, 2022), I first re-run the analysis with altered calibration thresholds for the causal conditions while leaving the calibration for the outcome unchanged. Specifically, I define the thresholds to be stricter about the inclusion and exclusion in the sets (Gupta et al., 2020). For example, instead of using the 25th percentile as the exclusion threshold and the 75th percentile for inclusion, I use the 10th and 90th percentiles, respectively. Furthermore, I apply a fuzzy calibration for institutional diversity, which was originally calibrated as crisp[44]. I provide an overview of the calibrations for this sensitivity analysis in Appendix 4.2.

For the models with the initial set of conditions, including both the bell-shaped as well as the logistic calibration for knowledge dissimilarity, consistency values drop slightly for some of the truth table rows considered in the Boolean minimization. However, the results remain qualitatively the same for the conservative 0.5% frequency cutoff. With the lower frequency cutoff, for the bell-shaped calibration of knowledge dissimilarity, one truth table row drops well below the consistency threshold, leading to the second configuration to become a subset of configuration (2) from Table 4.2. Similarly, when using a logistic calibration curve for knowledge dissimilarity, configuration (2) from Table 4.3 disappears entirely due to a significant drop in consistency for the respective truth table rows.

For the model with the two substituted conditions (i.e., domain experience for recombination novelty and prior collaboration for a central network position), consistency for the identified configurations remains high. However, with the 0.5% frequency cutoff, the previously included truth table row drops slightly below the threshold at 30 cases. Minimizing the truth table with this row included, despite it only having 27 cases assigned, reproduced

[44] I maintain the crisp calibration for domain experience due to the highly skewed distribution in which most cases exhibit no domain experience at all.

configuration (1a) from Table 4.4 but with both domain experience and prior collaboration emerging as core conditions. With the lower frequency cutoff, two of the originally considered truth table rows drop below the thresholds, while five other rows rise above the thresholds. These rows make the originally identified configurations (1b) and (3) more parsimonious (see Appendix 4.3). Consequently, they become supersets of the original configurations. Configuration (4) disappears from the configuration chart and is replaced by a newly emerging configuration. As a result, all configurations now show the presence of both domain experience and prior collaboration as part of the recipe for impactful innovations.

As a second robustness test, I recalibrate the outcome. Instead of comparing impactful innovations with non-impactful innovations (i.e., the vast majority of cases), I compare impactful innovations with particularly poor innovations (i.e., the least impactful cases). For that, I change the calibration threshold for the outcome to fully exclude all cases up to the 5th percentile and fully include cases at and above the 95th percentile, thereby creating balanced samples with cases from both tails of the distribution. I re-run the analysis for the configurations from Table 4.3 and Table 4.4 that emerged with the 0.5% frequency cutoff to verify whether the more common configurations held up. I use the original calibrations[45] for the causal conditions as well as the original sampling strategy and parameters for the analysis. For both the original set of conditions as well as the substitutions introduced in section 4.5.5, the exact same common configurations reemerge, including the delineation between core and peripheral conditions. Furthermore, the analysis on the negated outcome shows no consistent pathways to particularly poor innovation outcomes. I provide the truth tables for all robustness tests in Appendix 4.4.

The robustness tests demonstrate that the findings remain largely stable despite variations in calibration thresholds and adjustments to the outcome definition. While some configurations become subsets or supersets of the originals and certain rare configurations

[45] I conduct this additional analysis only with the logistic calibration for knowledge diversity, as it provides deeper insights into the role of knowledge diversity compared to the bell-shaped calibration.

disappear or are replaced after recalibrating the causal conditions, the overall results exhibit qualitative robustness, confirming the reliability of the analyses.

4.6 Discussion

In this chapter, I present a series of set-theoretic analyses (i.e., QCA) employing various parameters and model specifications to abductively examine the conjunctural effects of multiple interacting team-level conditions on the impact of innovation outcomes. The analysis is based on a dataset of several thousand clean energy patents, with each patent representing a unique innovation case and the distinct composition of its inventor team. Through a necessity analysis, I demonstrate that no single team composition attribute qualifies as a "must-have" for innovation teams to achieve impactful results. In a subsequent sufficiency analysis, by applying both a conservative as well as a lower frequency cutoff, I identify more common pathways along with rarer configurations that lead to impactful innovations. Yet, only a single, narrow common pathway emerges for each of the different models, highlighting that only very specific advantageous combinations of team composition factors are consistently linked to the creation of impactful innovation outcomes.

Building on empirical insights from prior studies suggesting an inverse U-shaped relationship between knowledge dissimilarity among team inventors and the impact of innovation outcomes (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020), I initially employed a bell-shaped calibration for knowledge dissimilarity, assigning set membership exclusively to cases with moderate levels of dissimilarity. However, the emerging configurations indicate the absence of moderate knowledge dissimilarity to be associated with impactful innovations. I therefore recalibrated the knowledge dissimilarity condition, assigning set membership to cases with high dissimilarity and non-membership to cases with low dissimilarity. Interestingly, and in contrast to findings from previous studies (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022, 2023; Vestal & Mesmer-Magnus, 2020), the recalibrated analysis reveals that low knowledge dissimilarity is more consistently linked to impactful innovation outcomes – when viewed in combination with other team-level conditions rather than in isolation. This may further indicate that, for clean energy technologies with their "complex character" (De Marchi, 2012, p. 615), a shared, in-depth understanding of the specific technological context is particularly important.

In addition to sharing similar knowledge bases, teams associated with impactful innovations also tend to recombine knowledge components in ways familiar to them, rather than engaging in exploratory activities, and exhibit only a few ties with inventors outside the team from past collaborations. To further investigate the roles of preexisting knowledge and collaborative ties, I conducted an additional analysis, substituting recombination novelty with domain experience and a central network position with prior collaborations among team members as alternate causal conditions. This analysis aimed to explore whether leveraging existing domain knowledge, which supports exploitation over exploration, and fostering strong internal rather than extensive external ties, enhances the likelihood of impactful innovation outcomes. The findings consistently highlight domain experience and prior collaborations as key building blocks for success. Furthermore, while teams with similar knowledge bases are generally more successful, some rare pathways to impactful innovations emerge where distant knowledge is effectively integrated – provided that domain experience and prior collaboration are present, reinforcing findings from recent studies (Vestal & Danneels, 2023). These results align with prior research demonstrating the importance of domain expertise and strong internal ties in enhancing integrative capacity (Jiao et al., 2022; Li et al., 2018; Schillebeeckx et al., 2019; Wang et al., 2017).

One of the rarest and most narrowly defined pathways to impactful innovations involves teams whose members frequently move between organizations of the same type but do not establish extensive collaborative ties with other inventors. This pattern suggests that these teams often transition organizational affiliations together, reinforcing the importance of shared collaboration experience. To delve deeper into this configuration, it is worth examining the cases represented by configuration (2) from Table 4.3. For each patent's first inventor, I compare their past patent assignees and co-inventorships with those of their collaborators. One illustrative example is patent *US5455458A*, co-filed by two inventors. Both inventors had previously worked for an aerospace company specializing in defense and communications electronics before it was acquired by a *General Motors* subsidiary focusing on automotive electronics. Following subsequent mergers, the company was restructured into a new independent entity. Throughout these transitions, the two inventors continued to co-develop technologies that later became foundational for subsequent innovations, including applications in clean energy. This exemplary case illustrates how maintaining continuity in collaborative relationships can contribute to the creation of impactful innovations.

4.6.1 Contributions

While various studies have investigated the effects of team composition factors on innovation outcomes, these studies have predominantly applied bivariate methods, focusing on the isolated impact of individual factors. However, innovation teams simultaneously combine multiple factors that interact in a causally complex way and likely allow for more than one specific team configuration to lead to particularly impactful innovation outcomes. Deeper insights into conjunctural effects and equally viable pathways to impactful innovations require a configurational perspective on innovation team composition that I introduce in this chapter.

My findings show multiple distinct, yet narrow pathways consistently associated with impactful innovation outcomes. While certain team composition factors emerge as generally beneficial, other factors appear to be advantageous only in certain configurations while being disadvantageous or irrelevant in others, highlighting the configurational and equifinal nature of innovation team composition. For example, factors such as knowledge dissimilarity (Cassi &

Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022, 2023; Vestal & Mesmer-Magnus, 2020) or a central position in the greater network of inventors (Yang et al., 2021), for which studies have collected solid empirical evidence showing a positive direct relationship with the impact of an innovation, reveal a more nuanced reality when considered through the lens of conjunctural causation. Furthermore, the analysis demonstrates that, while consistent recipes for impactful innovations exist, no team configuration consistently leads to non-impactful or particularly poor outcomes. Notably, even the inverse of configurations associated with success does not reliably produce poor results, reinforcing the principle of causal asymmetry. In summary, my analysis highlights the significant value of adopting a configurational perspective in understanding innovation team composition, offering new insights into the complex interplay of factors that drive impactful innovations, and advancing the field by moving beyond traditional approaches that focus on isolated marginal effects.

By demonstrating that teams producing impactful innovations often leverage their domain knowledge to effectively combine knowledge components in a familiar way – thereby engaging in exploitation – my findings challenge the emphasis on exploration as an antecedent of successful innovation in general (Bercovitz & Feldman, 2011), as well as for green innovation specifically (Marino & Quatraro, 2022), for the development of innovations with a significant impact on future technological advancements. On the other hand, my findings support the importance of continuity in co-inventorship, which facilitates the development of mutual understanding, the establishment of shared routines, and, thus, the effective integration of even distant knowledge (Jiao et al., 2022; Vestal & Danneels, 2023).

4.6.2 Practical Implications

The results of my analysis have important implications for the composition of innovation teams aiming to contribute foundational advancements in clean energy technologies. The identification of domain experience and prior collaboration as key ingredients of various causal recipes for impactful innovations emphasizes the value of involving inventors with experience innovating in the focal domain and fostering repeated co-inventorship within stable team constellations. Policymakers and managers should, therefore, actively support the development of well-established teams and minimize turnover that disrupts the cultivation of strong, enduring internal team bonds. This approach not only enhances the effectiveness of collaboration but also strengthens the integrative capacity required for achieving highly impactful innovation outcomes.

4.6.3 Limitations and Future Research

Despite its contributions, this study comes with limitations that should be acknowledged. First, to overcome the challenges arising from investigating impactful innovations which, by definition, represent a rare outcome, I artificially create balanced samples by oversampling on positive outcome cases (i.e., cases of impactful innovation). Furthermore, I increase contrast by only considering cases that are either fully in or fully out of the set of impactful innovations. Consequently, the balanced samples do not reflect the true prevalence of impactful innovations in the population and introduce a bias that limits the generalizability of the findings. Second, while it is common in the scholarly community to use patents as a proxy for innovation (see also Chapter 2), this practice often neglects that granted patents have already passed through a selective filtering process and, therefore, represent innovations that already meet specific criteria – such as novelty, utility, and non-obviousness. Moreover, some innovations – despite their value – are never patented due to, for example, strategic reasons (Scherer, 1983). However, patents remain well-suited for capturing impactful innovations as they require public disclosure of detailed technical knowledge, enabling others to build upon them and driving cumulative progress. Lastly, the selection of causal conditions in this study was guided by a novel, data-driven methodological approach. Although the chosen conditions consistently emerged as central across a wide range of models and subsamples derived from the broader population, it is possible that under different circumstances, an alternative set of causal conditions might better explain team configurations associated with impactful innovations.

As the theoretical landscape evolves and a stronger empirical foundation emerges to support a theory-informed selection of causal conditions, future research should revisit the configurational perspective on innovation team composition explored in this study. Additionally, this study focuses solely on one type of innovation outcome, leaving other significant outcomes, such as innovation *originality* or *green innovation*, underexplored. Investigating these alternative outcomes could provide equally valuable insights to guide policy development addressing the pressing technological challenges of our time. Conclusively, the insights this study provides on the value of letting teams grow into established, well-rehearsed units could be substantiated in future research through longitudinal studies that monitor team configurations and their corresponding innovation outcomes over time.

5. Conclusions and Future Research

In this dissertation, I adopt a configurational perspective to examine innovation team composition and its implications for the innovation outcome. With innovations increasingly emerging from the collective efforts of multiple inventors forming a team (Jones, 2009; Wuchty et al., 2007), scholarly interest in the antecedents of successful team-based innovation has grown over the past decades. This research focuses specifically on understanding the team composition factors contributing to particularly *impactful* innovations in the topical context of clean energy technologies. As the global climate crisis intensifies, greenhouse gas emissions urgently need to be reduced (IPCC, 2023). The energy sector remains the largest contributor to harmful emissions to date, calling for rapid advancements in clean energy technologies to mitigate the environmental impact of energy production on our climate (IEA, 2021). Therefore, it is in the vital interest of policymakers to foster those innovations that serve as foundational cornerstones for advancing technological trajectories in this domain.

Over the course of three main chapters (Chapters 2-4), I contribute to a deeper understanding of the causally complex interplay among team composition factors and their influence on different innovation outcomes, and on the *impact* of innovations specifically. In Chapter 2, I conduct a systematic review to summarize the current state of research on innovation team composition. This includes synthesizing empirical insights and resolving ambiguities arising from inconsistent measures and labels applied to team composition factors and the respective innovation outcomes investigated. The resulting comprehensive list of previously studied factors provides a foundation for analyzing the synergistic effects that arise when multiple factors interact within a team. However, the extensive range of team composition factors and the limited theoretical understanding of their relative importance require a systematic and rigorous selection process to identify a meaningful subset for further analysis. Common configurational methods typically rely on theoretical knowledge to select central causal conditions (Fiss, 2007). However, given the limited theoretical foundation in this context, I introduce a novel, data-driven approach in Chapter 3. This method systematically evaluates the performance of various specifications of set-analytic models, leveraging data from over 50,000 team-based clean energy patents. Through clustering, I identify factors that frequently co-occur in the best-performing models. These clusters highlight the factors that consistently emerge as central across a diverse range of models and randomly constructed samples, providing a robust basis for further analysis. Ultimately, in Chapter 4, I use the emerging set of factors to conduct a set-theoretic analysis using QCA. This analysis identifies team configurations (i.e., combinations of team composition factors) that are consistently linked to impactful innovation outcomes representing foundational building blocks for further technological advancements in the clean energy sector.

5.1 Key Findings and Contributions

This dissertation presents several important findings and makes significant contributions to the field of innovation management. By systematically mapping the current state of the literature, it identifies and addresses inconsistencies, ambiguities, and research gaps, providing researchers with critical leverage points for future studies. This work further lays the foundation for moving beyond an isolated understanding of individual factors' influences on different innovation outcomes towards a perspective that takes conjunctural effects into account. Furthermore, this dissertation introduces a novel methodological approach to overcome challenges in selecting central team composition factors arising from the lack of a substantive theoretical basis. Finally, it takes an important first step towards identifying specific team configurations – combinations of team composition factors – that are consistently linked to innovations with the greatest impact on future technological developments in the clean energy sector as a topical and relevant research context.

5.1.1 The Current State of the Literature

A systematic review of 54 articles published in leading journals in the field (Chapter 2) uncovered a diverse range of team composition factors and team-level innovation outcomes investigated in the extant literature on innovation team composition. However, prior studies have shown significant variability in the measures applied and notable inconsistencies in the terminology used to describe conceptually similar factors and outcomes. To address this issue, I conducted a *harmonization* process to establish thematic categories for both team composition factors and innovation outcomes, focusing on the measures employed rather than the original labels used by the authors. Through this effort, I derive 10 distinct categories of innovation outcomes and 17 categories of team composition factors, providing a clearer framework for organizing and integrating insights across studies.

Both team composition factors and innovation outcomes show significant variation in scholarly attention between thematic categories. Among the innovation outcomes, *innovation impact* emerges as the most frequently studied, serving as the primary outcome of interest in more than half of the articles in the sample (e.g., Cassi & Plunket, 2014; Chang, 2022; Jiao et al., 2022; Vestal & Danneels, 2023). Scholars have shown particular interest in the types of innovations that are most influential for subsequent inventors and researchers to build on. To measure impact, these studies predominantly use forward citations of patents or research papers. However, although applying very similar measures, there is considerable inconsistency in the terminology used to describe impactful innovations, ranging from directly relevant labels such as “invention impact” (e.g., Huo et al., 2019) to less precise expressions like “economic value” (Chang, 2022), and even to generic terms such as “team performance” (e.g., Ferrucci & Lissoni, 2019). Other outcome categories where inconsistent use of terminology is particularly pronounced include *innovation application scope*, *innovation output/productivity*, *innovation superiority*, and *innovation efficiency*. In contrast, terms are used more consistently in categories such as *commercial utilization* and *green innovation*, where the applied terminology tends to be clearer and more standardized.

Turning to team composition factors, prior studies have placed particular emphasis on understanding the role of *knowledge diversity* as an antecedent of successful team-based innovation. Scholars have extensively examined how the *variety* (e.g., Huo et al., 2019; Lee et al., 2015; Zaggl & Pottbäcker, 2021) and *dissimilarity* of knowledge (e.g., Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Mesmer-Magnus, 2020) within a team contribute to key outcomes, such as the impact, novelty, and originality of innovations. Scholars often use vector-based representations of individuals' knowledge bases by building on, for example, technological classes assigned to prior patents or keywords of past research articles published. Similarly, *demographic* aspects received much attention (e.g., Ferrucci & Lissoni, 2019; Kaltenberg et al., 2023; Marino & Quatraro, 2022), although research remains surprisingly sparser compared to literature that fucuses on investigating innovation outcomes on a department or firm level (e.g., Østergaard et al., 2011; Xie et al., 2020). While descriptive terminology is relatively consistent for some factors, such as *knowledge diversity* – largely due to their conceptual clarity – other factors exhibit overlaps in both concept and terminology that are more challenging to delineate (e.g., *organizational diversity* and *institutional diversity*). Furthermore, it is worth noting that a significant portion of team composition factors focus on diversity (e.g., knowledge, demographic, functional, and organizational diversity), highlighting the notion that varied perspectives and expertise are crucial drivers of innovation. At the same time, factors like *domain experience* and *prior collaboration* emphasize a team's capacity to effectively integrate these diverse perspectives.

Harmonizing both innovation outcomes and team composition factors from previous studies adds substantial value to the field. The inconsistent and unclear labeling of identical or conceptually similar measures makes it challenging to maintain a clear overview of the outcomes and factors studied, much less to integrate insights across studies. By deriving categorical themes, I address these ambiguities in the existing body of research, facilitating meaningful comparison and integration of empirical findings. Building on this foundation, I provide a qualitative synthesis of insights into the direct relationships between team composition factors and innovation outcomes. Notably, only a few relationships demonstrate a robust empirical basis, such as the curvilinear relationship between knowledge dissimilarity among team members and the impact of the innovation outcome (e.g., Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022). In contrast, other relationships, like the one between *team size* and impact, have been investigated in multiple studies but yield ambiguous results, while many relationships have been examined in only a handful of studies or remain largely unexplored.

Additionally, the review of the current state of the literature highlights a notable lack of attention to interaction effects. While some studies explore moderating factors, offering insights into the conditions under which certain effects are amplified or diminished, the majority remain focused on direct relationships. Similarly, mediating factors that could shed light on the underlying mechanisms have received little consideration. Moreover, the emphasis on direct relationships between individual factors is also reflected in the methods employed in existing studies. The vast majority of articles rely on bivariate (i.e., regression-based) methods, which analyze the effects of individual factors in isolation. This highlights critical limitations in the current research on innovation team composition and underscores significant gaps that must be addressed to develop a more holistic understanding of how team composition influences various team-level innovation outcomes. It also emphasizes the need for methodological diversity, particularly the use of approaches capable of uncovering conjunctural effects of multiple interacting factors rather than isolated effects alone.

5.1.2 Methodological Advancements

Traditional bivariate methods often fall short in capturing the nuanced interdependencies characteristic of causally complex phenomena. In contrast, set-theoretic approaches provide an analytical toolkit specifically designed to account for these complexities (Fiss, 2007; Ragin, 2000, 2008) by adopting a configurational perspective on causality (Mithas et al., 2022). However, commonly used set-theoretic methods, such as QCA, rely on the careful selection of causal conditions to produce interpretable causal pathways that explain an outcome of interest (Fiss, 2007). Typically, scholars rely on theory to identify a set of relevant conditions or, alternatively, draw insights directly from the cases (i.e., observed instances of the phenomenon under investigation). However, in certain research contexts – such as innovation team composition (see Chapter 2) – the theoretical landscape is characterized by a wide array of potential conditions coupled with limited or ambiguous insights into the relative significance or effects of these factors, making theory-driven selection particularly challenging. Furthermore, in large-N studies where a substantial number of empirical observations are analyzed, case-knowledge naturally becomes less accessible, reducing the utility of cases themselves in informing the selection of conditions (Greckhamer et al., 2013; Rutten, 2022). To address these challenges, this dissertation introduces a novel data-driven approach to condition selection specifically designed for such contexts (Chapter 3). This method employs the *Quine-McCluskey* algorithm, widely used in QCA for standard truth table minimization, and systematically evaluates all potential model specifications (i.e., combinations of conditions) based on the quality of their solutions (i.e., consistency and coverage; see Chapter 3 for details). To ensure robustness, model performance is assessed across multiple random subsamples, simulating "different realities", and across varying levels of model complexity (i.e., the number of conditions included). In a subsequent step, the best-performing models are clustered based on the overlap in causal conditions, identifying clusters of central conditions that frequently co-occur in the most effective models. Applying this new methodology to a dataset of over 50,000 team-based clean energy patents, along with a number of robustness tests, yields a set of seven causal conditions likely to hold genuine conjunctural causal significance. As a replicable method to identify the most relevant conditions for explaining outcomes, particularly in large-N studies with limited theoretical guidance and low case familiarity, this approach makes a valuable contribution to the scholarly community around QCA, and adjacent set-theoretic approaches more broadly. Beyond addressing the challenges arising from complex theoretical landscapes, this approach can also help resolve common critiques of unclear condition selection in QCA studies and enhance robustness and reliability of analyses more generally.

Additionally, this dissertation introduces a novel measure for knowledge (dissimilarity) to the innovation management literature. In the existing literature, particularly in studies utilizing patent data, it is common to represent the knowledge base of an individual or team using vector-based representations of the technology classes assigned to their past work and vector distance measures to determine knowledge dissimilarity between two entities (e.g., Melero & Palomeras, 2015; Singh & Fleming, 2010). However, this approach has significant limitations in resolution, as patents are often assigned to multiple technology classes simultaneously without any indication of their relative importance. As a result, the nuanced distribution of knowledge across different areas is lost, potentially obscuring important variations in the knowledge profiles of individuals or teams. I address this issue by using the actual textual content of prior work as *document embedding vector representation* to construct a centroid vector representation of an inventor's knowledge profile. Kelly et al. (2021) introduce a similar, wordcount-based approach to compare patents based on their textual contents. Yet, document embedding vectors use a trained machine-learning model to translate a text body into an N-dimensional vector representation of itself, based on its content and meaning, and have been shown to perform significantly better in capturing and comparing textual content than wordcount-based methods (A. M. Dai et al., 2015). This contribution equips the research community with a more nuanced and precise method for measuring knowledge (dissimilarity) – one of the most frequently studied antecedents of (team-based) innovation.

5.1.3 Insights from a Configurational Perspective

A growing body of research on innovation team composition has been exploring a wide array of factors and their effects on various innovation outcomes. However, most existing empirical studies emphasize the marginal impact of isolated factors, overlooking the complex interactions among them. To address this gap, this dissertation adopts a configurational perspective on innovation team composition, employing set-theoretic analysis, based on multiple thousand patents, to uncover several distinct, yet relatively narrow, causal pathways that lead to highly impactful innovations in the context of clean energy technologies (Chapter 4). While no causal condition or combinations thereof appear to be necessary "must-haves", a sufficiency analysis reveals several consistent but rare recipes for impactful clean energy innovations. These pathways provide numerous insights: Interestingly, and in contrast to prior studies suggesting an inverted U-shaped relationship where moderate *knowledge dissimilarity* among inventors appears to be optimal (Cassi & Plunket, 2014; Huo et al., 2019; Onal Vural et al., 2013; Vestal & Danneels, 2022; Vestal & Mesmer-Magnus, 2020), the set-theoretic analysis reveals that the *absence* of moderate dissimilarity (i.e., either low or high levels) is commonly associated with impactful innovations. A subsequent analysis, employing a recalibrated knowledge dissimilarity condition, further demonstrates that low knowledge dissimilarity, rather than high, is more consistently linked to such outcomes. Additionally, all identified pathways feature the *absence* of both *novel knowledge recombinations* and a *central network position* as conditions, with these factors even forming part of the causal core in the more common configurations. This suggests that teams that are associated with impactful clean energy innovations usually combine knowledge components in a way that is already familiar to them, emphasizing the importance of exploitation over exploration. Furthermore, the lack of a central network position shows that ties from previous collaborations to other inventors outside the team are not beneficial. Both findings diverge from prior research that rather highlights the value of exploration (e.g., Hubner et al., 2022; Li et al., 2018) and access to more inflow channels for knowledge resources (Yang et al., 2021). To further explore the roles of knowledge familiarity and tie formation, I conducted a supplemental analysis, replacing recombination novelty with *domain experience* and the central network position with *prior collaboration*. These substituted conditions represent conceptual counterparts to the original ones. Domain experience, in contrast to novel knowledge recombinations, reflects a high level of familiarity with the knowledge components utilized in a focal innovation. Similarly, prior collaborations among team inventors indicate stronger *internal* connections rather than external ties. The results of this supplemental analysis reinforce the earlier findings, demonstrating that domain experience and prior collaborations are fundamental building blocks for impactful innovation outcomes across various pathways. Furthermore, when both domain experience and prior collaborations are present, rare pathways emerge that incorporate dissimilar knowledge, highlighting how familiarity with the domain and a well-established internal team network facilitate the effective integration of even distant knowledge components. These findings provide important contributions to the understanding of innovation team composition, particularly within the context of clean energy technologies. They highlight that individual team composition factors cannot be examined in isolation but must be considered in conjunction with other conditions, revealing multiple equally viable causal pathways to impactful outcomes. Furthermore, by emphasizing the significance of familiarity with specific knowledge combinations, domain experience, and strong internal connections over external ties, this study challenges prevailing assumptions about the centrality of exploration and a deep embedding within the broader inventor network in driving impactful innovations.

5.2 Practical Implications

The findings of this dissertation have various practical implications for policymakers and managers that aim to foster particularly impactful innovation outcomes that serve as foundational building blocks for further developments in clean energy technologies. Throughout the three main chapters, this work enhances the understanding of how various team composition factors influence different types of innovation outcomes and, specifically, how multiple factors combine in different team configurations that are consistently associated with impactful innovations. The results of a configurational analysis highlight the important role of domain experience, knowledge exploitation rather than exploration, and repeated collaboration among inventors. Teams that accumulate experience innovating in the context of clean energy technologies and build strong relationships with co-inventors, thereby establishing a common understanding and shared routines, grow their capabilities to integrate knowledge effectively, enabling them to produce innovations with significant technological impact. Policymakers should, therefore, develop and implement strategies that actively incentivize experienced inventors to participate in innovation projects and sustain their engagement within the domain over time. Furthermore, they should prioritize minimizing turnover and actively support the formation of stable team constellations, enabling the accumulation of knowledge, the development of trust, and the establishment of efficient workflows. This can be facilitated through, for example, the provision of reliable long-term funding, the fostering of enduring partnerships, and the establishment of institutional conditions that support and encourage sustained collaboration among team members. Moreover, the results show that it is essential to embrace the complexity behind innovation team configurations, motivating policymakers and managers to think of team composition as an interplay of multiple conditions, where multiple pathways can lead to impactful innovation outcomes, rather than trying to implement one-size-fits-all strategies. By aligning with these insights, policymakers and managers can effectively foster impactful innovations and influence the pace at which clean energy solutions contribute to achieving the global net zero emissions goal.

5.3 Avenues for Future Research

This dissertation has made several important contributions while also uncovering promising directions for future research. First, the review of the existing literature on innovation team composition highlights a significant imbalance in scholarly attention across different team composition factors and types of team-level innovation outcomes. While factors like *knowledge diversity* have been extensively studied, other potentially impactful factors remain underexplored. Similarly, innovation outcomes, such as *innovation impact*, have been studied continuously over many years, whereas other important outcomes have received comparatively little attention. Future research should prioritize outcomes that are particularly relevant to addressing the grand challenges of our time, such as *green innovation*, to better understand the specific antecedents of these innovations. Moreover, interaction effects remain an underexplored area. Future research should focus on examining mediating, moderating, and contextual factors to better understand the underlying mechanisms driving these effects and the conditions under which they occur. The synthesis of existing empirical insights presented in Chapter 2 of this dissertation provides a framework to guide future exploration into promising research areas.

Furthermore, the systematic literature review highlights the overrepresentation of regression-based methods in studies examining the effects of team composition on innovation outcomes. While this dissertation introduces a configurational perspective, future research should continue to employ configurational methods that acknowledge the causally complex interplay of team composition factors and take conjunctural as well as equifinal and causally asymmetric effects into account. Yet, the theoretical landscape imposes significant challenges to the application of configurational approaches, especially to the selection of a limited set of causal conditions that are most relevant to explain the outcome of interest. This dissertation offers a methodological novelty to approach condition selection in a data-driven manner. However, future research should confirm the utility of this approach and further enhance it with respect to computational intensity and general applicability. Finally, as the theoretical foundation surrounding team composition factors continues to evolve, scholars should revisit traditional theory-based condition selection – not as a replacement but as a complementary approach to data-driven methodologies. In summary, this dissertation not only advances our understanding of innovation team composition but also lays the groundwork for future research to address existing gaps, embrace methodological diversity, and refine theoretical and empirical approaches to uncover the complex interplay of factors driving impactful innovation.

5.4 Conclusion

This dissertation adds a configurational perspective to the growing body of research on innovation team composition, using clean energy innovations as a topical research context. By systematically taking stock of the current state of literature in the field and synthesizing empirical findings on the effects of individual team composition factors on various innovation outcomes, this work establishes a foundation for exploring the conjunctural effects of multiple interacting factors. Moreover, it highlights key areas that remain underexplored, offering directions for future research. The broad yet shallow theoretical landscape that exists around the drivers of successful team-based innovation imposes significant challenges for the meaningful selection of a set of central causal conditions to look at inventor team composition form a configurational angle. This dissertation therefore introduces a novel method that addresses the condition selection through a data-driven approach. Based on a resulting set of conditions that are deemed particularly relevant for explaining team configurations that are associated with the most impactful innovation outcomes, and by leveraging an extensive sample of clean energy patents, this dissertation reveals multiple narrow pathways that consistently link to such outcomes and, thereby, equips policymakers with valuable insights into which team configurations to foster in order to accelerate advancements in clean energy technologies.

References

Acs, Z. J., & Audretsch, D. B. (1989). Patents as a Measure of Innovative Activity. *Kyklos*, *42*(2), 171–180. https://doi.org/10.1111/j.1467-6435.1989.tb00186.x

Aguinis, H., Ramani, R. S., & Alabduljader, N. (2018). What You See Is What You Get? Enhancing Methodological Transparency in Management Research. *Academy of Management Annals*, *12*(1), 83–110. https://doi.org/10.5465/annals.2016.0011

Ali, A., & Gittelman, M. (2016). Research Paradigms and Useful Inventions in Medicine: Patents and Licensing by Teams of Clinical and Basic Scientists in Academic Medical Centers. *Research Policy*, *45*(8), 1499–1511. https://doi.org/10.1016/j.respol.2016.03.015

Ardito, L., Natalicchio, A., Appio, F. P., & Messeni Petruzzelli, A. (2021). The Role of Scientific Knowledge Within Inventing Teams and the Moderating Effects of Team Internationalization and Team Experience: Empirical Tests Into the Aerospace Sector. *Journal of Business Research*, *128*, 701–710. https://doi.org/10.1016/j.jbusres.2019.11.022

Battaglia, D., Paolucci, E., & Ughetto, E. (2021). Opening the Black Box of University Proof-of-Concept Programs: Project and Team-Based Determinants of Research Commercialization Outcomes. *Technovation*, *108*, 1–15. https://doi.org/10.1016/j.technovation.2021.102334

Beaudry, C., & Schiffauerova, A. (2011). Impacts of Collaboration and Network Indicators on Patent Quality: The Case of Canadian Nanotechnology Innovation. *European Management Journal*, *29*(5), 362–376. https://doi.org/10.1016/j.emj.2011.03.001

Bercovitz, J., & Feldman, M. (2011). The Mechanisms of Collaboration in Inventive Teams: Composition, Social Networks, and Geography. *Research Policy*, *40*(1), 81–93. https://doi.org/10.1016/j.respol.2010.09.008

Blau, P. M. (1977). *Inequality and Heterogeneity: A Primitive Theory of Social Structure*. Free Press.

Boh, W. F., Evaristo, R., & Ouderkirk, A. (2014). Balancing Breadth and Depth of Expertise for Innovation: A 3M Story. *Research Policy*, *43*(2), 349–366. https://doi.org/10.1016/j.respol.2013.10.009

Brunetta, F., Marchegiani, L., & Peruffo, E. (2019). When Birds of a Feather Don't Flock Together: Diversity and Innovation Outcomes in International R&D Collaborations.

Journal of Business Research, *114*, 436–445. https://doi.org/10.1016/j.jbusres.2019.08.033

Capponi, G., Martinelli, A., & Nuvolari, A. (2022). Breakthrough Innovations and Where to Find Them. *Research Policy*, *51*(1), 1–15. https://doi.org/10.1016/j.respol.2021.104376

Caputo, F., Soto-Acosta, P., Chiacchierini, C., Mazzoleni, A., & Passaro, P. (2021). Smashing Local Boundaries for Sustaining Companies' Innovativeness: The Role of International R&D Teams. *Journal of Business Research*, *128*, 641–649. https://doi.org/10.1016/j.jbusres.2020.04.062

Carnabuci, G., & Operti, E. (2013). Where Do Firms' Recombinant Capabilities Come From? Intraorganizational Networks, Knowledge, and Firms' Ability to Innovate Through Technological Recombination. *Strategic Management Journal*, *34*(13), 1591–1613. https://doi.org/10.1002/smj.2084

Carpenter, M. P., Narin, F., & Woolf, P. (1981). Citation Rates to Technologically Important Patents. *World Patent Information*, *3*(4), 160–163. https://doi.org/10.1016/0172-2190(81)90098-3

Cassi, L., & Plunket, A. (2014). Proximity, Network Formation, and Inventive Performance: In Search of the Proximity Paradox. *The Annals of Regional Science*, *53*(2), 395–422. https://doi.org/10.1007/s00168-014-0612-6

Chang, M. H. (2022). Cascading Innovation: R&D Team Design and Performance Implications of Mobility. *Strategic Management Journal*, *44*(5), 1218–1253. https://doi.org/10.1002/smj.3473

Cheung, S. Y., Gong, Y., Wang, M., Le Zhou, & Shi, J. (2016). When and How Does Functional Diversity Influence Team Innovation? The Mediating Role of Knowledge Sharing and the Moderation Role of Affect-Based Trust in a Team. *Human Relations*, *69*(7), 1507–1531. https://doi.org/10.1177/0018726715615684

Choudhury, P., & Haas, M. R. (2018). Scope Versus Speed: Team Diversity, Leader Experience, and Patenting Outcomes for Firms. *Strategic Management Journal*, *39*(4), 977–1002. https://doi.org/10.1002/smj.2753

Choudhury, P., & Kim, D. Y. (2018). The Ethnic Migrant Inventor Effect: Codification and Recombination of Knowledge Across Borders. *Strategic Management Journal*, *40*(2), 203–229. https://doi.org/10.1002/smj.2977

Clarivate. (2024). *KeyWords Plus Generation, Creation, and Changes*. https://support.clarivate.com/ScientificandAcademicResearch/s/article/KeyWords-Plus-generation-creation-and-changes?language=en_US

Cowen, T. (2011). *The Great Stagnation: How America Ate All the Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better*. Dutton.

Cummings, J. N., & Kiesler, S. (2007). Coordination Costs and Project Outcomes in Multi-University Collaborations. *Research Policy*, *36*(10), 1620–1634. https://doi.org/10.1016/j.respol.2007.09.001

Czarnitzki, D., Hussinger, K., & Schneider, C. (2011). Commercializing Academic Research: The Quality of Faculty Patenting. *Industrial and Corporate Change*, *20*(5), 1403–1437. https://doi.org/10.1093/icc/dtr034

Dahlin, K. B., Weingart, L. R., & Hinds, P. J. (2005). Team Diversity and Information Use. *Academy of Management Journal*, *48*(6), 1107–1123. https://doi.org/10.5465/AMJ.2005.19573112

Dai, A. M., Olah, C., & Le, Q. V. (2015). *Document Embedding with Paragraph Vectors*. https://arxiv.org/pdf/1507.07998v1

Dai, Y., Byun, G., & Ding, F. (2019). The Direct and Indirect Impact of Gender Diversity in New Venture Teams on Innovation Performance. *Entrepreneurship Theory and Practice*, *43*(3), 505–528. https://doi.org/10.1177/1042258718807696

De Marchi, V. (2012). Environmental Innovation and R&D Cooperation: Empirical Evidence from Spanish Manufacturing Firms. *Research Policy*, *41*(3), 614–623. https://doi.org/10.1016/j.respol.2011.10.002

De Visser, M., Faems, D., Visscher, K., & De Weerd-Nederhof, P. (2014). The Impact of Team Cognitive Styles on Performance of Radical and Incremental NPD Projects. *Journal of Product Innovation Management*, *31*(6), 1167–1180. https://doi.org/10.1111/jpim.12247

Díaz-García, C., González-Moreno, A., & Jose Sáez-Martínez, F. (2013). Gender Diversity Within R&D Teams: Its Impact on Radicalness of Innovation. *Innovation*, *15*(2), 149–160. https://doi.org/10.5172/impp.2013.15.2.149

Dornbusch, F., & Neuhäusler, P. (2015). Composition of Inventor Teams and Technological Progress: The Role of Collaboration Between Academia and Industry. *Research Policy*, *44*(7), 1360–1375. https://doi.org/10.1016/j.respol.2015.04.003

Dosi, G. (1982). Technological Paradigms and Technological Trajectories. *Research Policy*, *11*(3), 147–162. https://doi.org/10.1016/0048-7333(82)90016-6

Dougherty, D. (1992). Interpretive Barriers to Successful Product Innovation in Large Firms. *Organization Science*, *3*(2), 179–202. https://doi.org/10.1287/orsc.3.2.179

Duşa, A. (2019). *QCA with R: A Comprehensive Resource*. Springer International Publishing.

Elsevier. (2024). *CiteScore*. https://www.elsevier.com/solutions/scopus/how-scopus-works/metrics/citescore

Ferrucci, E., & Lissoni, F. (2019). Foreign Inventors in Europe and the United States: Diversity and Patent Quality. *Research Policy*, *48*(9), 1–29. https://doi.org/10.1016/j.respol.2019.03.019

Fiss, P. C. (2007). A Set-Theoretic Approach to Organizational Configurations. *Academy of Management Review*, *32*(4), 1180–1198. https://doi.org/10.5465/amr.2007.26586092

Fiss, P. C. (2011). Building Better Causal Theories: A Fuzzy Set Approach to Typologies in Organization Research. *Academy of Management Journal*, *54*(2), 393–420. https://doi.org/10.5465/amj.2011.60263120

Fleming, L. (2001). Recombinant Uncertainty in Technological Search. *Management Science*, *47*(1), 117–132. https://doi.org/10.1287/mnsc.47.1.117.10671

Fleming, L., & Sorenson, O. (2004). Science as a Map in Technological Search. *Strategic Management Journal*, *25*(8-9), 909–928. https://doi.org/10.1002/smj.384

Franzoni, C., Scellato, G., & Stephan, P. (2018). Context Factors and the Performance of Mobile Individuals in Research Teams. *Journal of Management Studies*, *55*(1), 27–59. https://doi.org/10.1111/joms.12279

Freeman, R. B., & Huang, W. (2014). Collaboration: Strength in Diversity. *Nature*, *513*(7518), 305. https://doi.org/10.1038/513305a

Garcia Martinez, M., Zouaghi, F., & Garcia Marco, T. (2016). Diversity Is Strategy: The Effect of R&D Team Diversity on Innovative Performance. *R&D Management*, *47*(2), 311–329. https://doi.org/10.1111/radm.12244

Gates, B. (2022). https://www.breakthroughenergy.org

Gay, C., Latham, W., & Le Bas, C. (2008). Collective Knowledge, Prolific Inventors, and the Value of Inventions: An Empirical Study of French, German, and British Patents in the US, 1975–1999. *Economics of Innovation and New Technology*, *17*(1-2), 5–22. https://doi.org/10.1080/10438590701279193

Gittelman, M. (2007). Does Geography Matter for Science-Based Firms? Epistemic Communities and the Geography of Research and Patenting in Biotechnology. *Organization Science*, *18*(4), 724–741. https://doi.org/10.1287/orsc.1070.0249

Greckhamer, T. (2016). CEO Compensation in Relation to Worker Compensation Across Countries: The Configurational Impact of Country-Level Institutions. *Strategic Management Journal*, *37*(4), 793–815. https://doi.org/10.1002/smj.2370

Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying Configurations With Qualitative Comparative Analysis: Best Practices in Strategy and Organization Research. *Strategic Organization*, *16*(4), 482–495. https://doi.org/10.1177/1476127018786487

Greckhamer, T., Misangyi, V. F., Elms, H., & Lacey, R. (2008). Using Qualitative Comparative Analysis in Strategic Management Research. *Organizational Research Methods*, *11*(4), 695–726. https://doi.org/10.1177/1094428107302907

Greckhamer, T., Misangyi, V. F., & Fiss, P. C. (2013). The Two QCAs: From a Small-N to a Large-N Set Theoretic Approach. In P. C. Fiss, B. Cambré, & A. Marx (Eds.), *Research in the Sociology of Organizations. Configurational Theory and Methods in Organizational Research* (Vol. 38, pp. 49–75). Emerald Group Publishing Limited. https://doi.org/10.1108/S0733-558X(2013)0000038007

Gresov, C., & Drazin, R. (1997). Equifinality: Functional Equivalence in Organization Design. *Academy of Management Review*, *22*(2), 403–428. https://doi.org/10.5465/amr.1997.9707154064

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4), 1661–1707. https://doi.org/10.3386/w3301

Griliches, Z., Pakes, A., & Hall, B. (1986). *The Value of Patents as Indicators of Inventive Activity*.

Gupta, K., Crilly, D., & Greckhamer, T. (2020). Stakeholder Engagement Strategies, National Institutions, and Firm Performance: A Configurational Perspective. *Strategic Management Journal*, *41*(10), 1869–1900. https://doi.org/10.1002/smj.3204

Hargadon, A., & Sutton, R. I. (1997). Technology Brokering and Innovation in a Product Development Firm. *Administrative Science Quarterly*, *42*(4), 716–749. https://doi.org/10.2307/2393655

Harrison, D. A., & Klein, K. J. (2007). What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations. *Academy of Management Review*, *32*(4), 1199–1228. https://doi.org/10.5465/amr.2007.26586096

Harvey, S. (2014). Creative Synthesis: Exploring the Process of Extraordinary Group Creativity. *Academy of Management Review*, *39*(3), 324–343. https://doi.org/10.5465/amr.2012.0224

Haynes, P. (2014). Combining the Strengths of Qualitative Comparative Analysis with Cluster Analysis for Comparative Public Policy Research: With Reference to the Policy of

Economic Convergence in the Euro Currency Area. *International Journal of Public Administration*, *37*(9), 581–590. https://doi.org/10.1080/01900692.2014.880849

Henderson, R. M., & Clark, K. B. (1990). Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly*, *35*(1), 9–30. https://doi.org/10.2307/2393549

Hiebl, M. R. W. (2021). Sample Selection in Systematic Literature Reviews of Management Research. *Organizational Research Methods*, *26*(2), 229–261. https://doi.org/10.1177/1094428120986851

Hodson, R. (2017). Climate Change. *Nature*, *550*(7675), 53. https://doi.org/10.1038/550S53a

Hoegl, M., & Proserpio, L. (2004). Team Member Proximity and Teamwork in Innovative Projects. *Research Policy*, *33*(8), 1153–1165. https://doi.org/10.1016/j.respol.2004.06.005

Hoisl, K., Gruber, M., & Conti, A. (2016). R&D Team Diversity and Performance in Hypercompetitive Environments. *Strategic Management Journal*, *38*(7), 1455–1477. https://doi.org/10.1002/smj.2577

Hubner, S., Frese, M., Song, Z., Tripathi, N., Kaschner, T., & Le Kong, X. (2022). An Asia-Centric Approach to Team Innovation: Cultural Differences in Exploration and Exploitation Behavior. *Journal of Business Research*, *138*, 408–421. https://doi.org/10.1016/j.jbusres.2021.09.009

Hung, C.-L. (2017). Social Networks, Technology Ties, and Gatekeeper Functionality: Implications for the Performance Management of R&D Projects. *Research Policy*, *46*(1), 305–315. https://doi.org/10.1016/j.respol.2016.11.009

Huo, D., Motohashi, K., & Gong, H. (2019). Team Diversity as Dissimilarity and Variety in Organizational Innovation. *Research Policy*, *48*(6), 1564–1572. https://doi.org/10.1016/j.respol.2019.03.020

IEA. (2021). *Net Zero by 2050: A Roadmap for the Global Energy Sector*. IEA, Paris. https://www.iea.org/reports/net-zero-by-2050. https://www.iea.org/reports/net-zero-by-2050

IEA. (2022). *World Energy Outlook 2022*. IEA, Paris. https://www.iea.org/reports/world-energy-outlook-2022

IEA. (2023). *World Energy Outlook 2023*. IEA, Paris. https://www.iea.org/reports/world-energy-outlook-2023

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on

Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge, UK and New York, NY, USA. https://doi.org/10.1017/9781009325844

IPCC. (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647

Jain, A. (2013). Learning by Doing and the Locus of Innovative Capability in Biotechnology Research. *Organization Science*, *24*(6), 1683–1700. https://doi.org/10.1287/orsc.2013.0821

Jehn, K. A., Northcraft, G. B., & Neale, M. A. (1999). Why Differences Make a Difference: A Field Study of Diversity, Conflict and Performance in Workgroups. *Administrative Science Quarterly*, *44*(4), 741–763. https://doi.org/10.2307/2667054

Jiao, H., Wang, T., & Yang, J. (2022). Team Structure and Invention Impact Under High Knowledge Diversity: An Empirical Examination of the Computer Workstation Industry. *Technovation*, *114*, 1–12. https://doi.org/10.1016/j.technovation.2021.102449

Jones, B. F. (2009). The Burden of Knowledge and the “Death of the Renaissance Man”: Is Innovation Getting Harder? *Review of Economic Studies*, *76*(1), 283–317. https://doi.org/10.1111/j.1467-937X.2008.00531.x

Jones, B. F., Wuchty, S., & Uzzi, B. (2008). Multi-University Research Teams: Shifting Impact, Geography, and Stratification in Science. *Science (New York, N.Y.)*, *322*(5905), 1259–1262. https://doi.org/10.1126/science.1158357

Joshi, A., & Roh, H. (2009). The Role Of Context In Work Team Diversity Research: A Meta-Analytic Review. *Academy of Management Journal*, *52*(3), 599–627. https://doi.org/10.5465/amj.2009.41331491

Kaltenberg, M., Jaffe, A. B., & Lachman, M. E. (2023). Invention and the Life Course: Age Differences in Patenting. *Research Policy*, *52*(1), 1–16. https://doi.org/10.1016/j.respol.2022.104629

Katz, J., & Martin, B. R. (1997). What is Research Collaboration? *Research Policy*, *26*(1), 1–18. https://doi.org/10.1016/S0048-7333(96)00917-1

Kelly, B., Papanikolaou, D., Seru, A., & Taddy, M. (2021). Measuring Technological Innovation over the Long Run. *American Economic Review: Insights*, *3*(3), 303–320. https://doi.org/10.1257/aeri.20190499

Kerr, S. P., & Kerr, W. R. (2018). Global Collaborative Patents. *The Economic Journal*, *128*(612), 1-38. https://doi.org/10.1111/ecoj.12369

Kleinknecht, A., & Reinders, H. J. (2012). *How good are patents as innovation indicators? Evidence from German CIS data*. Oxford University Press Oxford, UK.

Kneeland, M. K., Schilling, M. A., & Aharonson, B. S. (2020). Exploring Uncharted Territory: Knowledge Search Processes in the Origination of Outlier Innovation. *Organization Science*, *31*(3), 535–557. https://doi.org/10.1287/orsc.2019.1328

Kozlowski, D., Murray, D. S., Bell, A., Hulsey, W., Larivière, V., Monroe-White, T., & Sugimoto, C. R. (2022). Avoiding Bias When Inferring Race Using Name-Based Approaches. *PloS One*, *17*(3), 1-16. https://doi.org/10.1371/journal.pone.0264270

Le Gallo, J., & Plunket, A. (2020). Regional Gatekeepers, Inventor Networks, and Inventive Performance: Spatial and Organizational Channels. *Research Policy*, *49*(5), 1–16. https://doi.org/10.1016/j.respol.2020.103981

Lee, Y.-N., Walsh, J. P., & Wang, J [Jian] (2015). Creativity in Scientific Teams: Unpacking Novelty and Impact. *Research Policy*, *44*(3), 684–697. https://doi.org/10.1016/j.respol.2014.10.007

Leppänen, P., George, G., & Alexy, O. (2023). When Do Novel Business Models Lead to High Performance? A Configurational Approach to Value Drivers, Competitive Strategy, and Firm Environment. *Academy of Management Journal*, *66*(1), Article amj.2020.0969, 164–194. https://doi.org/10.5465/amj.2020.0969

Li, D., Lin, J., Cui, W., & Qian, Y. (2018). The Trade-Off Between Knowledge Exploration and Exploitation in Technological Innovation. *Journal of Knowledge Management*, *22*(4), 781–801. https://doi.org/10.1108/JKM-09-2016-0401

MacCormack, A., Verganti, R., & Iansiti, M. (2001). Developing Products on "Internet Time": The Anatomy of a Flexible Development Process. *Management Science*, *47*(1), 133–150. https://doi.org/10.1287/mnsc.47.1.133.10663

Mackie, J. L. (1974). *The Cement of the Universe: A Study of Causation*. Clarendon Press.

Marino, A., & Quatraro, F. (2022). Leveraging Global Recombinant Capabilities for Green Technologies: The Role of Ethnic Diversity in MNEs' Dynamics. *The Journal of Technology Transfer*, *48*(4), 1413–1445. https://doi.org/10.1007/s10961-022-09975-5

Marx, A. (2010). Crisp-Set Qualitative Comparative Analysis (csQCA) and Model Specification: Benchmarks for Future csQCA Applications. *International Journal of Multiple Research Approaches*, *4*(2), 138–158. https://doi.org/10.5172/mra.2010.4.2.138

Maula, M., Heimeriks, K. H., & Keil, T. (2023). Organizational Experience and Performance: A Systematic Review and Contingency Framework. *Academy of Management Annals*, *17*(2), 546–585. https://doi.org/10.5465/annals.2021.0073

Melero, E., & Palomeras, N. (2015). The Renaissance Man Is Not Dead! The Role of Generalists in Teams of Inventors. *Research Policy*, *44*(1), 154–167. https://doi.org/10.1016/j.respol.2014.07.005

Meuer, J., & Rupietta, C. (2017). Integrating QCA and HLM for Multilevel Research on Organizational Configurations. *Organizational Research Methods*, *20*(2), 324–342. https://doi.org/10.1177/1094428116665465

Meuer, J., Rupietta, C., & Backes-Gellner, U. (2015). Layers of Co-Existing Innovation Systems. *Research Policy*, *44*(4), 888–910. https://doi.org/10.1016/j.respol.2015.01.013

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational Approaches to Organizational Analysis. *Academy of Management Journal*, *36*(6), 1175–1195. https://doi.org/10.5465/256809

Miric, M., & Fiss, P. C. (under review). *Antecedents of the Gender Gap in Technology Entrepreneurship: A Set-Analytic Approach*.

Misangyi, V. F., & Acharya, A. G. (2014). Substitutes or Complements? A Configurational Examination of Corporate Governance Mechanisms. *Academy of Management Journal*, *57*(6), 1681–1705. https://doi.org/10.5465/amj.2012.0728

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing Causal Complexity. *Journal of Management*, *43*(1), 255–282. https://doi.org/10.1177/0149206316679252

Mithas, S., Xue, L., Huang, N., & Burton-Jones, A. (2022). Editor's Comments: Causality Meets Diversity in Information Systems Research. *Management Information Systems Quarterly*, *46*(3), iii–xviii.

Monath, N., Jones, C., & Madhavan, S. (2021). *PatentsView: Disambiguating Inventors, Assignees, and Locations.* American Institutes for Research.

Muñoz, P., Gamble, E. N., & Beer, H. (2022). Impact Measurement in an Emerging Social Sector: Four Novel Approaches. *Academy of Management Discoveries*, *8*(2), 298–330. https://doi.org/10.5465/amd.2020.0044

Narin, F., & Breitzman, A. (1995). Inventive Productivity. *Research Policy*, *24*(4), 507–519. https://doi.org/10.1016/S0048-7333(94)00780-2

Nielsen, M. W., Bloch, C. W., & Schiebinger, L. (2018). Making Gender Diversity Work for Scientific Discovery and Innovation. *Nature Human Behaviour*, *2*(10), 726–734. https://doi.org/10.1038/s41562-018-0433-1

Nishii, L. H. (2013). The Benefits of Climate for Inclusion for Gender-Diverse Groups. *Academy of Management Journal*, *56*(6), 1754–1774. https://doi.org/10.5465/amj.2009.0823

Onal Vural, M., Dahlander, L., & George, G. (2013). Collaborative Benefits and Coordination Costs: Learning and Capability Development in Science. *Strategic Entrepreneurship Journal*, *7*(2), 122–137. https://doi.org/10.1002/sej.1154

Orsatti, G., Quatraro, F., & Pezzoni, M. (2020). The Antecedents of Green Technologies: The Role of Team-Level Recombinant Capabilities. *Research Policy*, *49*(3), 1–17. https://doi.org/10.1016/j.respol.2019.103919

Østergaard, C. R., Timmermans, B., & Kristinsson, K. (2011). Does a Different View Create Something New? The Effect of Employee Diversity on Innovation. *Research Policy*, *40*(3), 500–509. https://doi.org/10.1016/j.respol.2010.11.004

Park, M., Leahey, E., & Funk, R. J. (2023). Papers and Patents Are Becoming Less Disruptive Over Time. *Nature*, *613*(7942), 138–144. https://doi.org/10.1038/s41586-022-05543-x

Park, Y., Fiss, P. C., & El Sawy, O. A. (2020). Theorizing the Multiplicity of Digital Phenomena: The Ecology of Configurations, Causal Recipes, and Guidelines for Applying QCA. *MIS Quarterly*, *44*(4), 1493–1520. https://doi.org/10.25300/MISQ/2020/13879

Parmigiani, A., & King, E. (2019). Successfully Proposing and Composing Review Papers. *Journal of Management*, *45*(8), 3083–3090. https://doi.org/10.1177/0149206319874875

Perkmann, M., Salandra, R., Tartari, V., McKelvey, M., & Hughes, A. (2021). Academic Engagement: A Review of the Literature 2011-2019. *Research Policy*, *50*(1), 1–20. https://doi.org/10.1016/j.respol.2020.104114

Pfeifer, E., & Rocha, E. P. C. (2024). Phage-Plasmids Promote Recombination and Emergence of Phages and Plasmids. *Nature Communications*, *15*(1), 1–13. https://doi.org/10.1038/s41467-024-45757-3

Pollok, P., Amft, A., Diener, K., Lüttgens, D., & Piller, F. T. (2021). Knowledge Diversity and Team Creativity: How Hobbyists Beat Professional Designers in Creating Novel Board Games. *Research Policy*, *50*(8), 1–15. https://doi.org/10.1016/j.respol.2020.104174

Ragin, C. (2000). *Fuzzy-Set Social Science*. University of Chicago Press.

Ragin, C. (Ed.). (2008). *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. University of Chicago Press.

Rihoux, B., & De Meur, G. (2009). Crisp-Set Qualitative Comparative Analysis (csQCA). In B. Rihoux & C. Ragin (Eds.), *Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques* (pp. 33–68). SAGE Publications, Inc. https://doi.org/10.4135/9781452226569.n3

Rupietta, C., & Meuer, J. (2024). Comparative Configurational Process Analysis: A New Set-Theoretic Technique for Longitudinal Case Analysis. *Organizational Research Methods*, 1–28. https://doi.org/10.1177/10944281241259075

Rutten, R. (2022). Applying and Assessing Large-N QCA: Causality and Robustness From a Critical Realist Perspective. *Sociological Methods & Research*, *51*(3), 1211–1243. https://doi.org/10.1177/0049124120914955

Scherer, F. M. (1983). The Propensity to Patent. *International Journal of Industrial Organization*, *1*(1), 107–128. https://doi.org/10.1016/0167-7187(83)90026-7

Schillebeeckx, S. J. D., Lin, Y., & George, G. (2019). When Do Expert Teams Fail to Create Impactful Inventions? *Journal of Management Studies*, *56*(6), 1073–1104. https://doi.org/10.1111/joms.12447

Schmickl, C., & Kieser, A. (2008). How Much Do Specialists Have to Learn From Each Other When They Jointly Develop Radical Product Innovations? *Research Policy*, *37*(3), 473–491. https://doi.org/10.1016/j.respol.2007.12.001

Seo, E., Kang, H., & Song, J. (2020). Blending Talents for Innovation: Team Composition for Cross-Border R&D Collaboration Within Multinational Corporations. *Journal of International Business Studies*, *51*(5), 851–885. https://doi.org/10.1057/s41267-020-00331-z

Sethi, R. (2000). New Product Quality and Product Development Teams. *Journal of Marketing*, *64*(2), 1–14. https://doi.org/10.1509/jmkg.64.2.1.17999

Singh, J. (2008). Distributed R&D, Cross-Regional Knowledge Integration, and Quality of Innovative Output. *Research Policy*, *37*(1), 77–96. https://doi.org/10.1016/j.respol.2007.09.004

Singh, J., & Fleming, L. (2010). Lone Inventors as Sources of Breakthroughs: Myth or Reality? *Management Science*, *56*(1), 41–56. https://doi.org/10.1287/mnsc.1090.1072

Takalo, S. K., Tooranloo, H. S., & Parizi, Z. S. (2021). Green Innovation: A Systematic Literature Review. *Journal of Cleaner Production*, *279*, 1–22. https://doi.org/10.1016/j.jclepro.2020.122474

Taylor, A., & Greve, H. R. (2006). Superman or the Fantastic Four? Knowledge Combination and Experience in Innovative Teams. *Academy of Management Journal*, *49*(4), 723–740. https://doi.org/10.5465/amj.2006.22083029

Teodoridis, F., Bikard, M., & Vakili, K. (2019). Creativity at the Knowledge Frontier: The Impact of Specialization in Fast- and Slow-paced Domains. *Administrative Science Quarterly*, *64*(4), 894–927. https://doi.org/10.1177/0001839218793384

Toole, A. A., Saksena, M. J., deGrazia, C. A. W., Black, K. P., Lissoni, F., Miguelez, E., & Tarasconi, G. (2020). *Progress and Potential: 2020 Update on U.S. Women Inventor-Patentees.* U.S. Patent and Trademark Office.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The RAND Journal of Economics*, *21*(1), 172–187. https://doi.org/10.2307/2555502

Tzabbar, D., & Vestal, A. (2015). Bridging the Social Chasm in Geographically Distributed R&D Teams: The Moderating Effects of Relational Strength and Status Asymmetry on the Novelty of Team Innovation. *Organization Science*, *26*(3), 811–829. https://doi.org/10.1287/orsc.2015.0969

Usher, A. P. (1954). *A History of Mechanical Inventions*. Harvard University Press.

Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical Combinations and Scientific Impact. *Science (New York, N.Y.)*, *342*(6157), 468–472. https://doi.org/10.1126/science.1240474

Vakili, K., & Kaplan, S. (2021). Organizing for innovation: A contingency view on innovative team configuration. *Strategic Management Journal*, *42*(6), 1159–1183. https://doi.org/10.1002/smj.3264

Vedula, S., & Fitza, M. (2019). Regional Recipes: A Configurational Analysis of the Regional Entrepreneurial Ecosystem for U.S. Venture Capital-Backed Startups. *Strategy Science*, *4*(1), 4–24. https://doi.org/10.1287/stsc.2019.0076

Vestal, A., & Danneels, E. (2022). Technological Distance and Breakthrough Inventions in Multi-Cluster Teams: How Intra- and Inter-Location Ties Bridge the Gap. *Administrative Science Quarterly*, *67*(1), 167–206. https://doi.org/10.1177/00018392211027512

Vestal, A., & Danneels, E. (2023). Unlocking the Inventive Potential of Knowledge Distance in Teams: How Intrateam Network Configurations Provide a Key. *Organization Science*, *35*(1), 195–214. https://doi.org/10.1287/orsc.2023.1665

Vestal, A., & Mesmer-Magnus, J. (2020). Interdisciplinarity and Team Innovation: The Role of Team Experiential and Relational Resources. *Small Group Research*, *51*(6), 738–775. https://doi.org/10.1177/1046496420928405

Walsh, J. P., Lee, Y.-N., & Nagaoka, S. (2016). Openness and Innovation in the US: Collaboration Form, Idea Generation, and Implementation. *Research Policy*, *45*(8), 1660–1671. https://doi.org/10.1016/j.respol.2016.04.013

Wang, P., van de Vrande, V., & Jansen, J. J. (2017). Balancing Exploration and Exploitation in Inventions: Quality of Inventions and Team Composition. *Research Policy*, *46*(10), 1836–1850. https://doi.org/10.1016/j.respol.2017.09.002

WIPO. (2024). *IPC Green Inventory*. https://www.wipo.int/classifications/ipc/green-inventory/home

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The Increasing Dominance of Teams in Production of Knowledge, *316*(5827), 1036–1039. https://doi.org/10.1126/science.1136099

Xie, L., Zhou, J., Zong, Q., & Lu, Q. (2020). Gender Diversity in R&D Teams and Innovation Efficiency: Role of the Innovation Context. *Research Policy*, *49*(1), 1–13. https://doi.org/10.1016/j.respol.2019.103885

Yang, Y., She, Y., Hong, J., & Gan, Q. (2021). The Centrality and Innovation Performance of the Quantum High-Level Innovation Team: The Moderating Effect of Structural Holes. *Technology Analysis & Strategic Management*, *33*(11), 1332–1346. https://doi.org/10.1080/09537325.2021.1950676

Yildiz, H. E., Murtic, A., & Zander, U. (2024). Re-Conceptualizing Absorptive Capacity: The Importance of Teams as a Meso-Level Context. *Technological Forecasting and Social Change*, *199*, 1–13. https://doi.org/10.1016/j.techfore.2023.123039

Yoo, H. S., Jung, Y. L., & Jun, S.-P. (2023). The Effects of SMEs' R&D Team Diversity on Project-Level Performances: Evidence From South Korea's R&D Subsidy Program. *R&D Management*, *53*(3), 391–407. https://doi.org/10.1111/radm.12575

Zaggl, M. A., & Pottbäcker, J. (2021). Facilitators and Inhibitors for Integrating Expertise Diversity in Innovation Teams: The Case of Plasmid Exchange in Molecular Biology. *Research Policy*, *50*(9), 1–13. https://doi.org/10.1016/j.respol.2021.104313

Zhang, R., Wang, J [Jun], & Hao, J.-X. (2020). How Does Knowledge Heterogeneity Affect Transactive Memory System in Innovation? Evidence From a Field Study. *Journal of Knowledge Management*, *24*(8), 1965–1985. https://doi.org/10.1108/JKM-01-2020-0008

Zucker, L. G., Darby, M. R., & Armstrong, J. S. (2002). Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology. *Management Science*, *48*(1), 138–153. https://doi.org/10.1287/mnsc.48.1.138.14274

Appendix

Appendix Chapter 2

Appendix 2.1: List of Sources Considered for the Literature Review

1	Academy of Management Journal
2	Academy of Management Perspectives
3	Academy of Management Review
4	Administrative Science Quarterly
5	Asia and the Pacific Policy Studies
6	Asia Pacific Journal of Management
7	Asian Business and Management
8	British Journal of Management
9	BRQ Business Research Quarterly
10	Business Strategy and the Environment
11	California Management Review
12	Creative Industries Journal
13	Cross Cultural and Strategic Management
14	Economics of Innovation and New Technology
15	Entrepreneurial Business and Economics Review
16	Entrepreneurship & Regional Development
17	Entrepreneurship Theory and Practice
18	European Journal of Innovation Management
19	European Management Journal
20	European Research on Management and Business Economics
21	Foresight and STI Governance
22	Global Strategy Journal
23	Harvard Business Review
24	Human Relations
25	Human Resource Management
26	Industrial Management and Data Systems
27	Innovation: The European Journal of Social Science Research
28	International Entrepreneurship and Management Journal
29	International Journal of Entrepreneurial Behavior & Research
30	International Journal of Human Resource Management
31	International Journal of Management Reviews
32	International Journal of Operations and Production Management
33	International Journal of Project Management
34	International Small Business Journal
35	Journal of Business Research
36	Journal of Business Venturing
37	Journal of Engineering and Technology Management - JET-M
38	Journal of Industrial Integration and Management
39	Journal of Innovation & Knowledge
40	Journal of Intellectual Capital
41	Journal of International Management
42	Journal of Knowledge Management

43	Journal of Leadership and Organizational Studies	
44	Journal of Management	
45	Journal of Management in Engineering - ASCE	
46	Journal of Management Studies	
47	Journal of Open Innovation: Technology, Market, and Complexity	
48	Journal of Product Innovation Management	
49	Journal of Science and Technology Policy Management	
50	Journal of Small Business and Enterprise Development	
51	Journal of Small Business Management	
52	Long Range Planning	
53	Management Decision	
54	Management Review Quarterly	
55	Management Science	
56	New Technology, Work and Employment	
57	Omega	
58	Organization Science	
59	Organization Studies	
60	Organizational Behavior and Human Decision Processes	
61	R&D Management	
62	Research Policy	
63	Sloan Management Review	
64	Small Business Economics	
65	Socio-Economic Planning Sciences	
66	Strategic Entrepreneurship Journal	
67	Strategic Management Journal	
68	Strategic Organization	
69	Technological Forecasting and Social Change	
70	Technology Analysis & Strategic Management	
71	Technovation	
72	The Journal of Technology Transfer	
73	Industrial and Corporate Change	*
74	Journal of International Business Studies	*
75	Journal of Marketing	*
76	Nature	*
77	Science	*
78	Small Group Research	*
79	The Annals of Regional Science	*
80	The Economic Journal	*

Note: Sources marked with an asterisks (*) are not part of the initial source list but were added based on articles identified through the snowball sampling.

Appendix 2.2: List of Articles included in the Literature Review

	Reference	Source	Sampling Stage
1	Sethi (2000)	Journal of Marketing	Stage 2: Snowball
2	MacCormack et al. (2001)	Management Science	Stage 1: Scopus
3	Gittelman (2007)	Organization Science	Stage 2: Snowball
4	Cummings and Kiesler (2007)	Research Policy	Stage 2: Snowball
5	Wuchty et al. (2007)	Science	Stage 2: Snowball
6	Gay et al. (2008)	Economics of Innovation and New Technology	Stage 1: Scopus
7	Singh (2008)	Research Policy	Stage 1: Scopus
8	Jones et al. (2008)	Science	Stage 2: Snowball
9	Singh and Fleming (2010)	Management Science	Stage 1: Scopus
10	Beaudry and Schiffauerova (2011)	European Management Journal	Stage 1: Scopus
11	Bercovitz and Feldman (2011)	Research Policy	Stage 1: Scopus
12	Czarnitzki et al. (2011)	Industrial and Corporate Change	Stage 2: Snowball
13	Jain (2013)	Organization Science	Stage 1: Scopus
14	Onal Vural et al. (2013)	Strategic Entrepreneurship Journal	Stage 1: Scopus
15	Freeman and Huang (2014)	Nature	Stage 2: Snowball
16	Cassi and Plunket (2014)	The Annals of Regional Science	Stage 2: Snowball
17	Tzabbar and Vestal (2015)	Organization Science	Stage 1: Scopus
18	Dornbusch and Neuhäusler (2015)	Research Policy	Stage 1: Scopus
19	Melero and Palomeras (2015)	Research Policy	Stage 1: Scopus
20	Lee et al. (2015)	Research Policy	Stage 2: Snowball
21	Cheung et al. (2016)	Human Relations	Stage 1: Scopus
22	Ali and Gittelman (2016)	Research Policy	Stage 1: Scopus
23	Walsh et al. (2016)	Research Policy	Stage 2: Snowball
24	Wang et al. (2017)	Research Policy	Stage 1: Scopus
25	Hoisl et al. (2016)	Strategic Management Journal	Stage 1: Scopus
26	Hung (2017)	Research Policy	Stage 1: WoS
27	Li et al. (2018)	Journal of Knowledge Management	Stage 1: Scopus
28	Choudhury and Haas (2018)	Strategic Management Journal	Stage 1: Scopus
29	Choudhury and Kim (2018)	Strategic Management Journal	Stage 1: Scopus
30	Kerr and Kerr (2018)	The Economic Journal	Stage 2: Snowball
31	Franzoni et al. (2018)	Journal of Management Studies	Stage 1: WoS
32	Ferrucci and Lissoni (2019)	Research Policy	Stage 1: Scopus
33	Huo et al. (2019)	Research Policy	Stage 1: Scopus
34	Schillebeeckx et al. (2019)	Journal of Management Studies	Stage 1: Scopus
35	Brunetta et al. (2019)	Journal of Business Research	Stage 1: Scopus
36	Zhang et al. (2020)	Journal of Knowledge Management	Stage 1: Scopus
37	Kneeland et al. (2020)	Organization Science	Stage 1: Scopus
38	Orsatti et al. (2020)	Research Policy	Stage 1: Scopus
39	Le Gallo and Plunket (2020)	Research Policy	Stage 1: Scopus
40	Seo et al. (2020)	Journal of International Business Studies	Stage 2: Snowball
41	Vestal and Mesmer-Magnus (2020)	Small Group Research	Stage 2: Snowball
42	Zaggl and Pottbäcker (2021)	Research Policy	Stage 1: Scopus
43	Vakili and Kaplan (2021)	Strategic Management Journal	Stage 1: Scopus

44	Yang et al. (2021)	Technology Analysis and Strategic Management	Stage 1: Scopus
45	Battaglia et al. (2021)	Technovation	Stage 1: Scopus
46	Ardito et al. (2021)	Journal of Business Research	Stage 1: WoS
47	Hubner et al. (2022)	Journal of Business Research	Stage 1: Scopus
48	Marino and Quatraro (2022)	Journal of Technology Transfer	Stage 1: Scopus
49	Chang (2022)	Strategic Management Journal	Stage 1: Scopus
50	Jiao et al. (2022)	Technovation	Stage 1: Scopus
51	Vestal and Danneels (2022)	Administrative Science Quarterly	Stage 1: WoS
52	Kaltenberg et al. (2023)	Research Policy	Stage 1: Scopus
53	Vestal and Danneels (2023)	Organization Science	Stage 1: WoS
54	Yoo et al. (2023)	R&D Management	Stage 1: WoS

Appendix Chapter 3

Appendix 3.1: Negative Binomial Regression Summary

Model Info:
Observations: 57577
Dependent Variable: fwd5year
Type: Generalized linear model
  Family: Negative Binomial(0.4525)
  Link function: log

Model Fit:
$\chi^2(57537) = 3805.400$, $p = 0.000$
Pseudo-R^2 (Cragg-Uhler) = 0.064
Pseudo-R^2 (McFadden) = 0.013
AIC = 285990.169, BIC = 286357.565

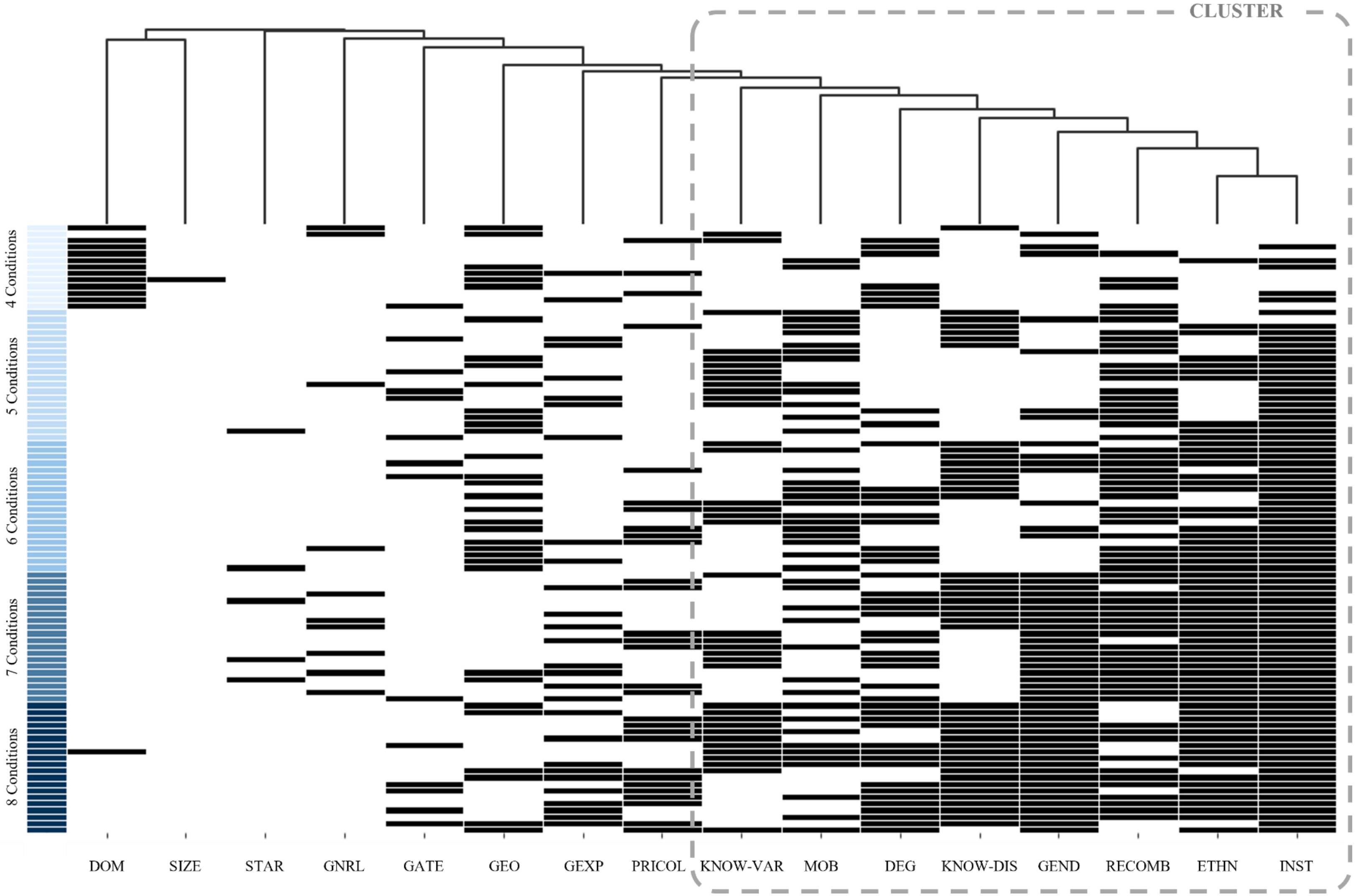
Standard errors:MLE

Variable	exp(Est.)	2.5%	97.5%	z val.	p	VIF
(Intercept)	2.7219	2.3474	3.1562	13.2580	0.0000	
domainfuels	1.2274	1.1609	1.2977	7.2111	0.0000	1.1289
domainfusion	0.7043	0.5867	0.8456	-3.7589	0.0002	1.1289
domaingeo	0.7107	0.5586	0.9041	-2.7804	0.0054	1.1289
domainhydro	0.7678	0.6703	0.8795	-3.8119	0.0001	1.1289
domainhydrogen	0.6470	0.6256	0.6691	-25.3703	0.0000	1.1289
domainpv	1.2257	1.1830	1.2700	11.2352	0.0000	1.1289
domainsea	1.0443	0.9088	1.2001	0.6114	0.5410	1.1289
domainsolar	1.5106	1.4008	1.6290	10.7133	0.0000	1.1289
domainwind	1.4378	1.3516	1.5296	11.5033	0.0000	1.1289
factor(year)1986	1.1327	0.9242	1.3882	1.2005	0.2299	1.1289
factor(year)1987	1.3285	1.0771	1.6385	2.6541	0.0080	1.1289
factor(year)1988	1.4334	1.1687	1.7580	3.4567	0.0005	1.1289
factor(year)1989	1.6063	1.3138	1.9640	4.6209	0.0000	1.1289
factor(year)1990	1.8756	1.5406	2.2834	6.2650	0.0000	1.1289
factor(year)1991	1.9856	1.6353	2.4110	6.9257	0.0000	1.1289
factor(year)1992	2.3983	1.9848	2.8980	9.0596	0.0000	1.1289
factor(year)1993	2.8422	2.3672	3.4125	11.1948	0.0000	1.1289
factor(year)1994	2.9693	2.4844	3.5487	11.9648	0.0000	1.1289
factor(year)1995	3.3703	2.8329	4.0095	13.7116	0.0000	1.1289
factor(year)1996	3.1725	2.6713	3.7677	13.1604	0.0000	1.1289
factor(year)1997	3.3318	2.8121	3.9476	13.9098	0.0000	1.1289
factor(year)1998	3.3557	2.8412	3.9633	14.2571	0.0000	1.1289
factor(year)1999	3.4692	2.9383	4.0960	14.6786	0.0000	1.1289
factor(year)2000	2.9877	2.5412	3.5127	13.2533	0.0000	1.1289
factor(year)2001	2.5603	2.1838	3.0016	11.5865	0.0000	1.1289
factor(year)2002	2.1991	1.8748	2.5795	9.6814	0.0000	1.1289
factor(year)2003	2.1423	1.8259	2.5135	9.3443	0.0000	1.1289
factor(year)2004	1.9768	1.6858	2.3180	8.3872	0.0000	1.1289
factor(year)2005	1.7695	1.5107	2.0726	7.0739	0.0000	1.1289

factor(year)2006	1.6039	1.3709	1.8765	5.8982	0.0000	1.1289
factor(year)2007	1.3786	1.1791	1.6120	4.0248	0.0001	1.1289
factor(year)2008	1.2095	1.0353	1.4130	2.3976	0.0165	1.1289
factor(year)2009	1.1979	1.0263	1.3981	2.2898	0.0220	1.1289
factor(year)2010	1.2121	1.0397	1.4129	2.4580	0.0140	1.1289
factor(year)2011	1.2862	1.1029	1.5000	3.2079	0.0013	1.1289
factor(year)2012	1.1420	0.9774	1.3344	1.6722	0.0945	1.1289
factor(year)2013	1.0268	0.8731	1.2076	0.3199	0.7490	1.1289
factor(year)2014	1.0532	0.8728	1.2709	0.5407	0.5887	1.1289
factor(year)2015	1.0940	0.7403	1.6168	0.4508	0.6521	1.1289

Appendix 3.2: Clustering Results with Linkage Method "average"

The alternate linkage method results in *inventor mobility (MOB)* showing a smaller distance to the core of the cluster compared to *knowledge variety (KNOW_VAR)*, making inventor mobility the 7th and knowledge variety the 8th condition.



Appendix 3.3: Model Performance Ranking

	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5	Condition 6	Condition 7	Condition 8	Consistency	Coverage	
1	KNOW_DIS	GEND	ETHN	INST	DEG	GNRL	RECOMB	-	0.8911	**0.1495**	
2	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	PRICOL	DEG	MOB	0.9045	**0.1453**	
3	KNOW_DIS	GEND	ETHN	INST	PRICOL	DEG	RECOMB	GEXP	0.8947	**0.1434**	
4	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	PRICOL	RECOMB	GEXP	0.8985	**0.1433**	
5	KNOW_DIS	GEND	ETHN	INST	DEG	RECOMB	GEXP	-	0.8963	**0.1422**	
6	KNOW_DIS	KNOW_VAR	GEND	ETHN	GEO	INST	DEG	MOB	0.8963	**0.1412**	
7	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	DEG	MOB	RECOMB	0.9020	**0.1407**	*
8	KNOW_DIS	GEND	ETHN	INST	PRICOL	DEG	GATE	GEXP	0.8879	**0.1402**	
9	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	PRICOL	MOB	RECOMB	0.8929	**0.1400**	
10	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	DEG	GATE	MOB	0.8887	**0.1397**	
11	KNOW_DIS	GEND	ETHN	INST	PRICOL	MOB	RECOMB	-	0.8962	**0.1391**	
12	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	PRICOL	DEG	RECOMB	0.9087	**0.1390**	
13	KNOW_DIS	KNOW_VAR	GEND	ETHN	INST	DEG	DOM	MOB	0.8882	**0.1389**	
14	KNOW_DIS	GEND	ETHN	INST	PRICOL	DEG	MOB	RECOMB	0.8982	**0.1373**	
15	KNOW_VAR	GEND	ETHN	GEO	INST	PRICOL	DEG	MOB	0.9060	**0.1360**	
16	KNOW_DIS	GEND	ETHN	INST	DEG	GATE	RECOMB	GEXP	0.8915	**0.1358**	
17	KNOW_DIS	GEND	ETHN	GEO	INST	PRICOL	RECOMB	GEXP	0.9029	**0.1355**	
18	KNOW_DIS	GEND	ETHN	INST	PRICOL	DEG	GATE	RECOMB	0.8959	**0.1353**	
19	KNOW_DIS	GEND	ETHN	INST	DEG	MOB	RECOMB	-	0.8962	**0.1349**	*
20	KNOW_VAR	GEND	ETHN	INST	DEG	RECOMB	GEXP	-	0.8823	**0.1348**	
…											

Note: Models that are part of the identified central cluster are marked with an asterisks (*). The table shows the 20 best-performing models among the total number of 38,506 models. The models are ranked based on the lower bound of the 95% confidence interval for model coverage.

Appendix 3.4: Supplemental Online Appendix

I provide the model performance summaries and the cluster plots for the robustness tests in an online appendix. For access, contact *niklas.hagenow(at)tum.de*.

Appendix Chapter 4

Appendix 4.1: Full Truth Tables

Appendix 4.1.1: Full truth table for configurations associated with **impactful innovations**; **initial model specification** for moderate knowledge dissimilarity (bell-shaped calibration); the assigned outcome values for more common configurations with a conservative frequency cutoff of 0.5 % (30 cases) are listed under “cons.”; outcome values for rarer configurations with a frequency cutoff of 2 cases are listed under “rare”.

	Conditions							**OUT**			**Consistency**			**PRI**		
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	cons.	rare	N	raw	mean	90% CI	raw	mean	90% CI
(1)	0	0	0	0	0	0	0	0	0	52	0.54	0.54	[0.54,0.55]	0.54	0.54	[0.54,0.55]
(2)	0	0	0	0	0	0	1	?	0	16	0.59	0.57	[0.56,0.59]	0.59	0.57	[0.56,0.59]
(3)	0	0	0	0	0	1	0	0	0	42	0.38	0.38	[0.37,0.38]	0.38	0.38	[0.37,0.38]
(4)	0	0	0	0	0	1	1	0	0	41	0.38	0.41	[0.40,0.42]	0.38	0.41	[0.40,0.42]
(5)	0	0	0	0	1	0	0	0	0	367	0.41	0.42	[0.42,0.43]	0.41	0.42	[0.42,0.43]
(6)	0	0	0	0	1	0	1	0	0	72	0.46	0.47	[0.46,0.47]	0.46	0.47	[0.46,0.47]
(7)	0	0	0	0	1	1	0	0	0	106	0.53	0.50	[0.50,0.51]	0.53	0.50	[0.50,0.51]
(8)	0	0	0	0	1	1	1	0	0	72	0.39	0.40	[0.39,0.40]	0.39	0.40	[0.39,0.40]
(9)	0	0	0	1	0	0	0	?	0	14	0.56	0.52	[0.51,0.53]	0.56	0.52	[0.51,0.53]
(10)	0	0	0	1	0	0	1	?	0	19	0.67	0.66	[0.65,0.67]	0.67	0.66	[0.65,0.67]
(11)	0	0	0	1	0	1	0	0	0	33	0.47	0.48	[0.47,0.49]	0.47	0.48	[0.47,0.49]
(12)	0	0	0	1	0	1	1	0	0	34	0.49	0.47	[0.46,0.48]	0.49	0.47	[0.46,0.48]
(13)	0	0	0	1	1	0	0	0	0	281	0.48	0.45	[0.45,0.46]	0.48	0.45	[0.45,0.46]
(14)	0	0	0	1	1	0	1	0	0	122	0.42	0.42	[0.42,0.43]	0.42	0.42	[0.42,0.43]
(15)	0	0	0	1	1	1	0	0	0	133	0.51	0.52	[0.51,0.52]	0.51	0.52	[0.51,0.52]
(16)	0	0	0	1	1	1	1	0	0	108	0.45	0.44	[0.44,0.45]	0.45	0.44	[0.44,0.45]
(17)	0	0	1	0	0	0	0	?	0	8	0.60	0.59	[0.57,0.61]	0.60	0.59	[0.57,0.61]
(18)	0	0	1	0	0	0	1	?	0	5	0.61	0.61	[0.59,0.63]	0.61	0.61	[0.59,0.63]
(19)	0	0	1	0	0	1	0	?	0	13	0.45	0.47	[0.46,0.49]	0.45	0.47	[0.46,0.49]
(20)	0	0	1	0	0	1	1	?	0	9	0.33	0.36	[0.35,0.37]	0.33	0.36	[0.35,0.37]
(21)	0	0	1	0	1	0	0	0	0	104	0.39	0.40	[0.40,0.41]	0.39	0.40	[0.40,0.41]

(22)	0	0	1	0	1	0	1	?	0	21	0.47	0.43	[0.42,0.44]	0.47	0.43	[0.42,0.44]
(23)	0	0	1	0	1	1	0	0	0	32	0.35	0.44	[0.43,0.45]	0.35	0.44	[0.43,0.45]
(24)	0	0	1	0	1	1	1	?	0	24	0.36	0.42	[0.41,0.43]	0.36	0.42	[0.41,0.43]
(25)	0	0	1	1	0	0	0	?	0	2	0.45	0.38	[0.37,0.39]	0.45	0.38	[0.37,0.39]
(26)	0	0	1	1	0	0	1	?	0	4	0.65	0.62	[0.60,0.64]	0.65	0.62	[0.60,0.64]
(27)	0	0	1	1	0	1	0	?	0	12	0.37	0.41	[0.39,0.42]	0.37	0.41	[0.39,0.42]
(28)	0	0	1	1	0	1	1	?	0	14	0.71	0.64	[0.62,0.65]	0.71	0.64	[0.62,0.65]
(29)	0	0	1	1	1	0	0	0	0	94	0.43	0.43	[0.42,0.44]	0.43	0.43	[0.42,0.44]
(30)	0	0	1	1	1	0	1	0	0	32	0.32	0.34	[0.33,0.35]	0.32	0.34	[0.33,0.35]
(31)	0	0	1	1	1	1	0	0	0	39	0.33	0.40	[0.39,0.41]	0.33	0.40	[0.39,0.41]
(32)	0	0	1	1	1	1	1	?	0	24	0.31	0.36	[0.35,0.37]	0.31	0.36	[0.35,0.37]
(33)	0	1	0	0	0	0	0	?	0	13	0.66	0.61	[0.59,0.62]	0.66	0.61	[0.59,0.62]
(34)	0	1	0	0	0	0	1	?	0	18	0.76	0.74	[0.73,0.76]	0.76	0.74	[0.73,0.76]
(35)	0	1	0	0	0	1	0	?	0	23	0.34	0.31	[0.30,0.32]	0.34	0.31	[0.30,0.32]
(36)	0	1	0	0	0	1	1	?	0	24	0.30	0.30	[0.29,0.31]	0.30	0.30	[0.29,0.31]
(37)	0	1	0	0	1	0	0	0	0	156	0.54	0.51	[0.50,0.51]	0.54	0.51	[0.50,0.51]
(38)	0	1	0	0	1	0	1	0	0	56	0.47	0.44	[0.43,0.45]	0.47	0.44	[0.43,0.45]
(39)	0	1	0	0	1	1	0	0	0	70	0.50	0.49	[0.48,0.50]	0.50	0.49	[0.48,0.50]
(40)	0	1	0	0	1	1	1	0	0	63	0.36	0.35	[0.34,0.35]	0.36	0.35	[0.34,0.35]
(41)	0	1	0	1	0	0	0	?	0	6	0.62	0.57	[0.56,0.59]	0.62	0.57	[0.56,0.59]
(42)	0	1	0	1	0	0	1	?	0	5	0.78	0.66	[0.65,0.67]	0.78	0.66	[0.65,0.67]
(43)	0	1	0	1	0	1	0	0	0	33	0.47	0.49	[0.48,0.50]	0.47	0.49	[0.48,0.50]
(44)	0	1	0	1	0	1	1	0	0	72	0.63	0.63	[0.62,0.63]	0.63	0.63	[0.62,0.63]
(45)	0	1	0	1	1	0	0	0	0	157	0.52	0.52	[0.52,0.53]	0.52	0.52	[0.52,0.53]
(46)	0	1	0	1	1	0	1	0	0	79	0.45	0.47	[0.46,0.47]	0.45	0.47	[0.46,0.47]
(47)	0	1	0	1	1	1	0	0	0	91	0.49	0.49	[0.48,0.49]	0.49	0.49	[0.48,0.49]
(48)	0	1	0	1	1	1	1	0	0	72	0.36	0.36	[0.35,0.36]	0.36	0.36	[0.35,0.36]
(49)	0	1	1	0	0	0	0	?	0	4	0.30	0.42	[0.39,0.44]	0.30	0.42	[0.39,0.44]
(50)	0	1	1	0	0	0	1	?	1	2	0.83	0.84	[0.82,0.85]	0.83	0.84	[0.82,0.85]
(51)	0	1	1	0	0	1	0	?	0	10	0.50	0.44	[0.42,0.46]	0.50	0.44	[0.42,0.46]

(52)	0	1	1	0	0	1	1	?	0	6	0.35	0.32	[0.31,0.34]	0.35	0.32	[0.31,0.34]
(53)	0	1	1	0	1	0	0	0	0	43	0.48	0.44	[0.43,0.45]	0.48	0.44	[0.43,0.45]
(54)	0	1	1	0	1	0	1	?	0	29	0.56	0.56	[0.55,0.58]	0.56	0.56	[0.55,0.58]
(55)	0	1	1	0	1	1	0	0	0	36	0.51	0.55	[0.54,0.56]	0.51	0.55	[0.54,0.56]
(56)	0	1	1	0	1	1	1	0	0	34	0.31	0.39	[0.38,0.40]	0.31	0.39	[0.38,0.40]
(57)	0	1	1	1	0	0	0	?	0	2	0.37	0.36	[0.35,0.38]	0.37	0.36	[0.35,0.38]
(58)	0	1	1	1	0	0	1	?	1	6	0.89	0.84	[0.82,0.85]	0.89	0.84	[0.82,0.85]
(59)	0	1	1	1	0	1	0	?	0	17	0.44	0.43	[0.42,0.44]	0.44	0.43	[0.42,0.44]
(60)	0	1	1	1	0	1	1	?	0	12	0.52	0.55	[0.53,0.56]	0.52	0.55	[0.53,0.56]
(61)	0	1	1	1	1	0	0	0	0	64	0.48	0.49	[0.48,0.50]	0.48	0.49	[0.48,0.50]
(62)	0	1	1	1	1	0	1	?	0	25	0.41	0.50	[0.49,0.52]	0.41	0.50	[0.49,0.52]
(63)	0	1	1	1	1	1	0	0	0	31	0.43	0.45	[0.45,0.46]	0.43	0.45	[0.45,0.46]
(64)	0	1	1	1	1	1	1	?	0	25	0.37	0.40	[0.39,0.41]	0.37	0.40	[0.39,0.41]
(65)	1	0	0	0	0	0	0	1	1	41	0.80	0.79	[0.78,0.80]	0.80	0.79	[0.78,0.80]
(66)	1	0	0	0	0	0	1	1	1	48	0.79	0.79	[0.78,0.80]	0.79	0.79	[0.78,0.80]
(67)	1	0	0	0	0	1	0	0	0	60	0.68	0.70	[0.69,0.71]	0.68	0.70	[0.69,0.71]
(68)	1	0	0	0	0	1	1	0	0	74	0.55	0.54	[0.54,0.55]	0.55	0.54	[0.54,0.55]
(69)	1	0	0	0	1	0	0	0	0	105	0.60	0.62	[0.62,0.63]	0.60	0.62	[0.62,0.63]
(70)	1	0	0	0	1	0	1	0	0	128	0.60	0.59	[0.59,0.60]	0.60	0.59	[0.59,0.60]
(71)	1	0	0	0	1	1	0	0	0	55	0.66	0.66	[0.66,0.67]	0.66	0.66	[0.66,0.67]
(72)	1	0	0	0	1	1	1	0	0	121	0.52	0.51	[0.51,0.52]	0.52	0.51	[0.51,0.52]
(73)	1	0	0	1	0	0	0	?	0	11	0.63	0.61	[0.60,0.62]	0.63	0.61	[0.60,0.62]
(74)	1	0	0	1	0	0	1	0	0	35	0.61	0.65	[0.64,0.66]	0.61	0.65	[0.64,0.66]
(75)	1	0	0	1	0	1	0	0	0	35	0.62	0.63	[0.63,0.64]	0.62	0.63	[0.63,0.64]
(76)	1	0	0	1	0	1	1	0	0	103	0.64	0.62	[0.62,0.63]	0.64	0.62	[0.62,0.63]
(77)	1	0	0	1	1	0	0	0	0	135	0.54	0.53	[0.53,0.54]	0.54	0.53	[0.53,0.54]
(78)	1	0	0	1	1	0	1	0	0	171	0.51	0.53	[0.52,0.53]	0.51	0.53	[0.52,0.53]
(79)	1	0	0	1	1	1	0	0	0	76	0.57	0.61	[0.60,0.62]	0.57	0.61	[0.60,0.62]
(80)	1	0	0	1	1	1	1	0	0	141	0.51	0.52	[0.52,0.53]	0.51	0.52	[0.52,0.53]
(81)	1	0	1	0	0	0	0	?	0	2	0.82	0.55	[0.53,0.58]	0.82	0.55	[0.53,0.58]

(82)	1	0	1	0	0	0	1	?	0	2	0.57	0.46	[0.44,0.48]	0.57	0.46	[0.44,0.48]
(83)	1	0	1	0	0	1	0	?	0	17	0.79	0.73	[0.71,0.74]	0.79	0.73	[0.71,0.74]
(84)	1	0	1	0	0	1	1	?	0	21	0.55	0.55	[0.53,0.56]	0.55	0.55	[0.53,0.56]
(85)	1	0	1	0	1	0	0	0	0	42	0.52	0.58	[0.57,0.58]	0.52	0.58	[0.57,0.58]
(86)	1	0	1	0	1	0	1	0	0	38	0.48	0.48	[0.47,0.49]	0.48	0.48	[0.47,0.49]
(87)	1	0	1	0	1	1	0	?	0	21	0.63	0.58	[0.57,0.59]	0.63	0.58	[0.57,0.59]
(88)	1	0	1	0	1	1	1	0	0	37	0.42	0.42	[0.41,0.43]	0.42	0.42	[0.41,0.43]
(89)	1	0	1	1	0	0	0	?	?	1	0.55	0.38	[0.36,0.40]	0.55	0.38	[0.36,0.40]
(90)	1	0	1	1	0	0	1	?	0	2	0.41	0.29	[0.28,0.30]	0.41	0.29	[0.28,0.30]
(91)	1	0	1	1	0	1	0	?	0	8	0.58	0.56	[0.54,0.57]	0.58	0.56	[0.54,0.57]
(92)	1	0	1	1	0	1	1	?	0	11	0.41	0.38	[0.36,0.39]	0.41	0.38	[0.36,0.39]
(93)	1	0	1	1	1	0	0	0	0	32	0.37	0.43	[0.42,0.44]	0.37	0.43	[0.42,0.44]
(94)	1	0	1	1	1	0	1	0	0	30	0.32	0.36	[0.35,0.36]	0.32	0.36	[0.35,0.36]
(95)	1	0	1	1	1	1	0	?	0	21	0.60	0.59	[0.58,0.60]	0.60	0.59	[0.58,0.60]
(96)	1	0	1	1	1	1	1	0	0	36	0.55	0.55	[0.54,0.56]	0.55	0.55	[0.54,0.56]
(97)	1	1	0	0	0	0	0	?	0	2	0.64	0.55	[0.53,0.58]	0.64	0.55	[0.53,0.58]
(98)	1	1	0	0	0	0	1	?	0	9	0.58	0.57	[0.55,0.59]	0.58	0.57	[0.55,0.59]
(99)	1	1	0	0	0	1	0	?	0	20	0.74	0.65	[0.64,0.67]	0.74	0.65	[0.64,0.67]
(100)	1	1	0	0	0	1	1	0	0	77	0.59	0.56	[0.55,0.57]	0.59	0.56	[0.55,0.57]
(101)	1	1	0	0	1	0	0	0	0	41	0.68	0.62	[0.62,0.63]	0.68	0.62	[0.62,0.63]
(102)	1	1	0	0	1	0	1	0	0	95	0.54	0.53	[0.52,0.53]	0.54	0.53	[0.52,0.53]
(103)	1	1	0	0	1	1	0	0	0	32	0.61	0.62	[0.61,0.63]	0.61	0.62	[0.61,0.63]
(104)	1	1	0	0	1	1	1	0	0	146	0.43	0.44	[0.44,0.45]	0.43	0.44	[0.44,0.45]
(105)	1	1	0	1	0	0	0	?	0	5	0.47	0.54	[0.52,0.56]	0.47	0.54	[0.52,0.56]
(106)	1	1	0	1	0	0	1	?	0	16	0.62	0.63	[0.62,0.64]	0.62	0.63	[0.62,0.64]
(107)	1	1	0	1	0	1	0	?	0	15	0.57	0.57	[0.55,0.58]	0.57	0.57	[0.55,0.58]
(108)	1	1	0	1	0	1	1	0	0	89	0.48	0.51	[0.51,0.52]	0.48	0.51	[0.51,0.52]
(109)	1	1	0	1	1	0	0	0	0	51	0.56	0.54	[0.53,0.55]	0.56	0.54	[0.53,0.55]
(110)	1	1	0	1	1	0	1	0	0	68	0.53	0.55	[0.54,0.56]	0.53	0.55	[0.54,0.56]
(111)	1	1	0	1	1	1	0	0	0	37	0.49	0.54	[0.53,0.55]	0.49	0.54	[0.53,0.55]

(112)	1	1	0	1	1	1	1	0	0	64	0.43	0.40	[0.39,0.40]	0.43	0.40	[0.39,0.40]
(113)	1	1	1	0	0	0	0	?	0	3	0.74	0.73	[0.71,0.75]	0.74	0.73	[0.71,0.75]
(114)	1	1	1	0	0	0	1	?	0	4	0.31	0.46	[0.44,0.49]	0.31	0.46	[0.44,0.49]
(115)	1	1	1	0	0	1	0	?	0	14	0.66	0.64	[0.63,0.66]	0.66	0.64	[0.63,0.66]
(116)	1	1	1	0	0	1	1	0	0	30	0.42	0.50	[0.49,0.51]	0.42	0.50	[0.49,0.51]
(117)	1	1	1	0	1	0	0	0	0	34	0.70	0.69	[0.68,0.70]	0.70	0.69	[0.68,0.70]
(118)	1	1	1	0	1	0	1	0	0	44	0.65	0.60	[0.60,0.61]	0.65	0.60	[0.60,0.61]
(119)	1	1	1	0	1	1	0	?	0	21	0.57	0.58	[0.57,0.59]	0.57	0.58	[0.57,0.59]
(120)	1	1	1	0	1	1	1	0	0	46	0.46	0.46	[0.45,0.47]	0.46	0.46	[0.45,0.47]
(121)	1	1	1	1	0	0	0	?	0	3	0.42	0.49	[0.47,0.51]	0.42	0.49	[0.47,0.51]
(122)	1	1	1	1	0	0	1	?	0	6	0.44	0.52	[0.50,0.54]	0.44	0.52	[0.50,0.54]
(123)	1	1	1	1	0	1	0	?	0	10	0.72	0.65	[0.64,0.67]	0.72	0.65	[0.64,0.67]
(124)	1	1	1	1	0	1	1	?	0	20	0.53	0.49	[0.48,0.51]	0.53	0.49	[0.48,0.51]
(125)	1	1	1	1	1	0	0	0	0	34	0.58	0.63	[0.62,0.64]	0.58	0.63	[0.62,0.64]
(126)	1	1	1	1	1	0	1	?	0	26	0.56	0.59	[0.58,0.60]	0.56	0.59	[0.58,0.60]
(127)	1	1	1	1	1	1	0	?	0	24	0.53	0.59	[0.58,0.60]	0.53	0.59	[0.58,0.60]
(128)	1	1	1	1	1	1	1	0	0	40	0.57	0.61	[0.60,0.62]	0.57	0.61	[0.60,0.62]

Appendix 4.1.2: Full truth table for configurations associated with **impactful innovations**; model specification with **recalibrated knowledge dissimilarity** condition; the assigned outcome values for more common configurations with a conservative frequency cutoff of 0.5 % (30 cases) are listed under “cons.”; outcome values for rarer configurations with a frequency cutoff of 2 cases are listed under “rare”.

	Conditions							OUT			Consistency			PRI		
	INST	ETHN	GEND	KNOW_DIS	RECOMB	DEG	MOB	cons.	rare	N	raw	mean	90% CI	raw	mean	90% CI
(1)	0	0	0	0	0	0	0	0	0	58	0.53	0.53	[0.52,0.53]	0.53	0.53	[0.52,0.53]
(2)	0	0	0	0	0	0	1	?	0	27	0.68	0.62	[0.61,0.63]	0.68	0.62	[0.61,0.63]
(3)	0	0	0	0	0	1	0	0	0	53	0.43	0.41	[0.40,0.41]	0.43	0.41	[0.40,0.41]
(4)	0	0	0	0	0	1	1	0	0	53	0.50	0.50	[0.49,0.51]	0.50	0.50	[0.49,0.51]
(5)	0	0	0	0	1	0	0	0	0	498	0.43	0.43	[0.42,0.43]	0.43	0.43	[0.42,0.43]
(6)	0	0	0	0	1	0	1	0	0	104	0.47	0.46	[0.46,0.46]	0.47	0.46	[0.46,0.46]
(7)	0	0	0	0	1	1	0	0	0	148	0.53	0.50	[0.50,0.50]	0.53	0.50	[0.50,0.50]
(8)	0	0	0	0	1	1	1	0	0	110	0.45	0.45	[0.45,0.46]	0.45	0.45	[0.45,0.46]
(9)	0	0	0	1	0	0	0	?	0	8	0.65	0.62	[0.61,0.63]	0.65	0.62	[0.61,0.63]
(10)	0	0	0	1	0	0	1	?	0	8	0.55	0.60	[0.59,0.61]	0.55	0.60	[0.59,0.61]
(11)	0	0	0	1	0	1	0	?	0	22	0.50	0.53	[0.52,0.54]	0.50	0.53	[0.52,0.54]
(12)	0	0	0	1	0	1	1	?	0	22	0.43	0.43	[0.42,0.44]	0.43	0.43	[0.42,0.44]
(13)	0	0	0	1	1	0	0	0	0	150	0.50	0.48	[0.48,0.49]	0.50	0.48	[0.48,0.49]
(14)	0	0	0	1	1	0	1	0	0	90	0.40	0.42	[0.41,0.42]	0.40	0.42	[0.41,0.42]
(15)	0	0	0	1	1	1	0	0	0	91	0.52	0.55	[0.55,0.56]	0.52	0.55	[0.55,0.56]
(16)	0	0	0	1	1	1	1	0	0	70	0.41	0.40	[0.40,0.41]	0.41	0.40	[0.40,0.41]
(17)	0	0	1	0	0	0	0	?	0	10	0.54	0.51	[0.49,0.52]	0.54	0.51	[0.49,0.52]
(18)	0	0	1	0	0	0	1	?	0	5	0.60	0.57	[0.54,0.59]	0.60	0.57	[0.54,0.59]
(19)	0	0	1	0	0	1	0	?	0	12	0.45	0.42	[0.41,0.43]	0.45	0.42	[0.41,0.43]
(20)	0	0	1	0	0	1	1	?	0	14	0.59	0.57	[0.56,0.58]	0.59	0.57	[0.56,0.58]
(21)	0	0	1	0	1	0	0	0	0	135	0.39	0.41	[0.41,0.42]	0.39	0.41	[0.41,0.42]
(22)	0	0	1	0	1	0	1	?	0	13	0.41	0.38	[0.37,0.39]	0.41	0.38	[0.37,0.39]
(23)	0	0	1	0	1	1	0	0	0	42	0.30	0.38	[0.37,0.39]	0.30	0.38	[0.37,0.39]
(24)	0	0	1	0	1	1	1	?	0	18	0.30	0.33	[0.32,0.34]	0.30	0.33	[0.32,0.34]
(25)	0	0	1	1	0	0	0	?	?	0	-	0.47	[0.45,0.49]	-	0.47	[0.45,0.49]

(26)	0	0	1	1	0	0	1	?	0	4	0.69	0.65	[0.63,0.67]	0.69	0.65	[0.63,0.67]
(27)	0	0	1	1	0	1	0	?	0	13	0.40	0.47	[0.45,0.48]	0.40	0.47	[0.45,0.48]
(28)	0	0	1	1	0	1	1	?	0	9	0.67	0.59	[0.57,0.60]	0.67	0.59	[0.57,0.60]
(29)	0	0	1	1	1	0	0	0	0	63	0.45	0.42	[0.42,0.43]	0.45	0.42	[0.42,0.43]
(30)	0	0	1	1	1	0	1	0	0	40	0.37	0.39	[0.38,0.40]	0.37	0.39	[0.38,0.40]
(31)	0	0	1	1	1	1	0	?	0	29	0.36	0.42	[0.41,0.43]	0.36	0.42	[0.41,0.43]
(32)	0	0	1	1	1	1	1	0	0	30	0.35	0.40	[0.39,0.41]	0.35	0.40	[0.39,0.41]
(33)	0	1	0	0	0	0	0	?	0	16	0.68	0.61	[0.60,0.62]	0.68	0.61	[0.60,0.62]
(34)	0	1	0	0	0	0	1	?	0	8	0.68	0.59	[0.57,0.61]	0.68	0.59	[0.57,0.61]
(35)	0	1	0	0	0	1	0	0	0	36	0.38	0.39	[0.38,0.40]	0.38	0.39	[0.38,0.40]
(36)	0	1	0	0	0	1	1	0	0	57	0.60	0.63	[0.62,0.64]	0.60	0.63	[0.62,0.64]
(37)	0	1	0	0	1	0	0	0	0	185	0.52	0.50	[0.50,0.50]	0.52	0.50	[0.50,0.50]
(38)	0	1	0	0	1	0	1	0	0	40	0.49	0.48	[0.47,0.49]	0.49	0.48	[0.47,0.49]
(39)	0	1	0	0	1	1	0	0	0	80	0.47	0.46	[0.45,0.46]	0.47	0.46	[0.45,0.46]
(40)	0	1	0	0	1	1	1	0	0	36	0.36	0.35	[0.35,0.36]	0.36	0.35	[0.35,0.36]
(41)	0	1	0	1	0	0	0	?	0	3	0.69	0.62	[0.60,0.63]	0.69	0.62	[0.60,0.63]
(42)	0	1	0	1	0	0	1	?	0	15	0.80	0.72	[0.71,0.74]	0.80	0.72	[0.71,0.74]
(43)	0	1	0	1	0	1	0	?	0	20	0.52	0.50	[0.49,0.51]	0.52	0.50	[0.49,0.51]
(44)	0	1	0	1	0	1	1	0	0	39	0.51	0.47	[0.46,0.48]	0.51	0.47	[0.46,0.48]
(45)	0	1	0	1	1	0	0	0	0	128	0.52	0.53	[0.53,0.53]	0.52	0.53	[0.53,0.53]
(46)	0	1	0	1	1	0	1	0	0	95	0.44	0.44	[0.43,0.44]	0.44	0.44	[0.43,0.44]
(47)	0	1	0	1	1	1	0	0	0	81	0.52	0.52	[0.52,0.53]	0.52	0.52	[0.52,0.53]
(48)	0	1	0	1	1	1	1	0	0	99	0.35	0.35	[0.35,0.36]	0.35	0.35	[0.35,0.36]
(49)	0	1	1	0	0	0	0	?	0	4	0.26	0.28	[0.27,0.30]	0.26	0.28	[0.27,0.30]
(50)	0	1	1	0	0	0	1	?	1	8	0.80	0.79	[0.77,0.80]	0.80	0.79	[0.77,0.80]
(51)	0	1	1	0	0	1	0	?	0	15	0.46	0.43	[0.42,0.44]	0.46	0.43	[0.42,0.44]
(52)	0	1	1	0	0	1	1	?	0	6	0.50	0.53	[0.52,0.55]	0.50	0.53	[0.52,0.55]
(53)	0	1	1	0	1	0	0	0	0	51	0.43	0.41	[0.40,0.42]	0.43	0.41	[0.40,0.42]
(54)	0	1	1	0	1	0	1	?	0	10	0.34	0.41	[0.40,0.43]	0.34	0.41	[0.40,0.43]
(55)	0	1	1	0	1	1	0	?	0	26	0.48	0.47	[0.46,0.48]	0.48	0.47	[0.46,0.48]

(56)	0	1	1	0	1	1	1	?	0	12	0.37	0.36	[0.35,0.37]	0.37	0.36	[0.35,0.37]
(57)	0	1	1	1	0	0	0	?	0	2	0.46	0.44	[0.42,0.45]	0.46	0.44	[0.42,0.45]
(58)	0	1	1	1	0	0	1	?	?	0	-	0.76	[0.75,0.78]	-	0.76	[0.75,0.78]
(59)	0	1	1	1	0	1	0	?	0	12	0.49	0.45	[0.44,0.46]	0.49	0.45	[0.44,0.46]
(60)	0	1	1	1	0	1	1	?	0	12	0.58	0.54	[0.53,0.56]	0.58	0.54	[0.53,0.56]
(61)	0	1	1	1	1	0	0	0	0	56	0.51	0.51	[0.50,0.51]	0.51	0.51	[0.50,0.51]
(62)	0	1	1	1	1	0	1	0	0	44	0.53	0.58	[0.57,0.59]	0.53	0.58	[0.57,0.59]
(63)	0	1	1	1	1	1	0	0	0	41	0.44	0.49	[0.48,0.50]	0.44	0.49	[0.48,0.50]
(64)	0	1	1	1	1	1	1	0	0	47	0.34	0.41	[0.40,0.42]	0.34	0.41	[0.40,0.42]
(65)	1	0	0	0	0	0	0	1	1	49	0.76	0.75	[0.75,0.76]	0.76	0.75	[0.75,0.76]
(66)	1	0	0	0	0	0	1	1	1	67	0.73	0.75	[0.74,0.75]	0.73	0.75	[0.74,0.75]
(67)	1	0	0	0	0	1	0	0	0	55	0.69	0.67	[0.66,0.67]	0.69	0.67	[0.66,0.67]
(68)	1	0	0	0	0	1	1	0	0	96	0.61	0.59	[0.59,0.60]	0.61	0.59	[0.59,0.60]
(69)	1	0	0	0	1	0	0	0	0	119	0.54	0.55	[0.55,0.56]	0.54	0.55	[0.55,0.56]
(70)	1	0	0	0	1	0	1	0	0	130	0.53	0.55	[0.55,0.56]	0.53	0.55	[0.55,0.56]
(71)	1	0	0	0	1	1	0	0	0	64	0.60	0.63	[0.62,0.63]	0.60	0.63	[0.62,0.63]
(72)	1	0	0	0	1	1	1	0	0	124	0.56	0.56	[0.55,0.56]	0.56	0.56	[0.55,0.56]
(73)	1	0	0	1	0	0	0	?	0	3	0.57	0.56	[0.55,0.57]	0.57	0.56	[0.55,0.57]
(74)	1	0	0	1	0	0	1	?	0	16	0.59	0.66	[0.65,0.67]	0.59	0.66	[0.65,0.67]
(75)	1	0	0	1	0	1	0	0	0	40	0.61	0.68	[0.67,0.69]	0.61	0.68	[0.67,0.69]
(76)	1	0	0	1	0	1	1	0	0	81	0.60	0.60	[0.60,0.61]	0.60	0.60	[0.60,0.61]
(77)	1	0	0	1	1	0	0	0	0	121	0.57	0.58	[0.57,0.58]	0.57	0.58	[0.57,0.58]
(78)	1	0	0	1	1	0	1	0	0	169	0.55	0.55	[0.55,0.55]	0.55	0.55	[0.55,0.55]
(79)	1	0	0	1	1	1	0	0	0	67	0.59	0.63	[0.63,0.64]	0.59	0.63	[0.63,0.64]
(80)	1	0	0	1	1	1	1	0	0	138	0.48	0.49	[0.48,0.49]	0.48	0.49	[0.48,0.49]
(81)	1	0	1	0	0	0	0	?	?	1	0.64	0.40	[0.38,0.42]	0.64	0.40	[0.38,0.42]
(82)	1	0	1	0	0	0	1	?	?	0	-	0.29	[0.27,0.30]	-	0.29	[0.27,0.30]
(83)	1	0	1	0	0	1	0	?	0	19	0.75	0.71	[0.70,0.72]	0.75	0.71	[0.70,0.72]
(84)	1	0	1	0	0	1	1	?	0	15	0.53	0.56	[0.54,0.57]	0.53	0.56	[0.54,0.57]
(85)	1	0	1	0	1	0	0	?	0	22	0.43	0.49	[0.48,0.50]	0.43	0.49	[0.48,0.50]

(86)	1	0	1	0	1	0	1	?	0	14	0.30	0.34	[0.33,0.35]	0.30	0.34	[0.33,0.35]
(87)	1	0	1	0	1	1	0	?	0	21	0.61	0.62	[0.61,0.63]	0.61	0.62	[0.61,0.63]
(88)	1	0	1	0	1	1	1	?	0	28	0.52	0.57	[0.56,0.58]	0.52	0.57	[0.56,0.58]
(89)	1	0	1	1	0	0	0	?	0	2	0.62	0.49	[0.47,0.51]	0.62	0.49	[0.47,0.51]
(90)	1	0	1	1	0	0	1	?	0	4	0.41	0.37	[0.36,0.39]	0.41	0.37	[0.36,0.39]
(91)	1	0	1	1	0	1	0	?	0	6	0.60	0.59	[0.57,0.60]	0.60	0.59	[0.57,0.60]
(92)	1	0	1	1	0	1	1	?	0	17	0.49	0.44	[0.43,0.45]	0.49	0.44	[0.43,0.45]
(93)	1	0	1	1	1	0	0	0	0	52	0.44	0.51	[0.50,0.52]	0.44	0.51	[0.50,0.52]
(94)	1	0	1	1	1	0	1	0	0	54	0.43	0.44	[0.43,0.45]	0.43	0.44	[0.43,0.45]
(95)	1	0	1	1	1	1	0	?	0	21	0.60	0.57	[0.56,0.58]	0.60	0.57	[0.56,0.58]
(96)	1	0	1	1	1	1	1	0	0	45	0.47	0.45	[0.45,0.46]	0.47	0.45	[0.45,0.46]
(97)	1	1	0	0	0	0	0	?	0	5	0.41	0.48	[0.46,0.50]	0.41	0.48	[0.46,0.50]
(98)	1	1	0	0	0	0	1	?	0	14	0.61	0.63	[0.62,0.65]	0.61	0.63	[0.62,0.65]
(99)	1	1	0	0	0	1	0	?	0	21	0.69	0.66	[0.65,0.67]	0.69	0.66	[0.65,0.67]
(100)	1	1	0	0	0	1	1	0	0	68	0.57	0.59	[0.58,0.59]	0.57	0.59	[0.58,0.59]
(101)	1	1	0	0	1	0	0	?	0	29	0.52	0.51	[0.50,0.52]	0.52	0.51	[0.50,0.52]
(102)	1	1	0	0	1	0	1	0	0	37	0.50	0.56	[0.55,0.57]	0.50	0.56	[0.55,0.57]
(103)	1	1	0	0	1	1	0	0	0	34	0.46	0.56	[0.54,0.57]	0.46	0.56	[0.54,0.57]
(104)	1	1	0	0	1	1	1	0	0	50	0.46	0.47	[0.46,0.47]	0.46	0.47	[0.46,0.47]
(105)	1	1	0	1	0	0	0	?	0	2	0.58	0.59	[0.57,0.61]	0.58	0.59	[0.57,0.61]
(106)	1	1	0	1	0	0	1	?	0	11	0.57	0.59	[0.57,0.60]	0.57	0.59	[0.57,0.60]
(107)	1	1	0	1	0	1	0	?	0	14	0.55	0.54	[0.52,0.55]	0.55	0.54	[0.52,0.55]
(108)	1	1	0	1	0	1	1	0	0	98	0.50	0.51	[0.51,0.52]	0.50	0.51	[0.51,0.52]
(109)	1	1	0	1	1	0	0	0	0	63	0.64	0.60	[0.59,0.61]	0.64	0.60	[0.59,0.61]
(110)	1	1	0	1	1	0	1	0	0	126	0.53	0.52	[0.51,0.52]	0.53	0.52	[0.51,0.52]
(111)	1	1	0	1	1	1	0	0	0	35	0.58	0.58	[0.57,0.59]	0.58	0.58	[0.57,0.59]
(112)	1	1	0	1	1	1	1	0	0	160	0.41	0.41	[0.40,0.41]	0.41	0.41	[0.40,0.41]
(113)	1	1	1	0	0	0	0	?	0	2	0.83	0.74	[0.71,0.76]	0.83	0.74	[0.71,0.76]
(114)	1	1	1	0	0	0	1	?	0	9	0.42	0.63	[0.60,0.66]	0.42	0.63	[0.60,0.66]
(115)	1	1	1	0	0	1	0	?	0	13	0.82	0.72	[0.71,0.74]	0.82	0.72	[0.71,0.74]

(116)	1	1	1	0	0	1	1	?	0	10	0.47	0.49	[0.48,0.50]	0.47	0.49	[0.48,0.50]
(117)	1	1	1	0	1	0	0	?	0	19	0.65	0.68	[0.67,0.69]	0.65	0.68	[0.67,0.69]
(118)	1	1	1	0	1	0	1	?	0	7	0.51	0.57	[0.55,0.58]	0.51	0.57	[0.55,0.58]
(119)	1	1	1	0	1	1	0	?	0	17	0.56	0.62	[0.61,0.63]	0.56	0.62	[0.61,0.63]
(120)	1	1	1	0	1	1	1	?	0	14	0.54	0.60	[0.58,0.61]	0.54	0.60	[0.58,0.61]
(121)	1	1	1	1	0	0	0	?	0	4	0.38	0.49	[0.46,0.51]	0.38	0.49	[0.46,0.51]
(122)	1	1	1	1	0	0	1	?	?	1	0.39	0.44	[0.43,0.46]	0.39	0.44	[0.43,0.46]
(123)	1	1	1	1	0	1	0	?	0	11	0.64	0.64	[0.63,0.65]	0.64	0.64	[0.63,0.65]
(124)	1	1	1	1	0	1	1	0	0	40	0.51	0.54	[0.53,0.55]	0.51	0.54	[0.53,0.55]
(125)	1	1	1	1	1	0	0	0	0	49	0.62	0.64	[0.63,0.65]	0.62	0.64	[0.63,0.65]
(126)	1	1	1	1	1	0	1	0	0	63	0.63	0.60	[0.59,0.61]	0.63	0.60	[0.59,0.61]
(127)	1	1	1	1	1	1	0	?	0	28	0.54	0.58	[0.58,0.59]	0.54	0.58	[0.58,0.59]
(128)	1	1	1	1	1	1	1	0	0	72	0.51	0.52	[0.51,0.52]	0.51	0.52	[0.51,0.52]

Appendix 4.1.3: Full truth table for configurations associated with **impactful innovations**; model specification with **recalibrated knowledge dissimilarity** and **substituted conditions**; the assigned outcome values for more common configurations with a conservative frequency cutoff of 0.5 % (30 cases) are listed under “cons.”; outcome values for rarer configurations with a frequency cutoff of 5 cases are listed under “rare”.

	Conditions							OUT			Consistency			PRI		
	INST	ETHN	GEND	KNOW_DIS	DOM	PRICOL	MOB	cons.	rare	N	raw	mean	90% CI	raw	mean	90% CI
(1)	0	0	0	0	0	0	0	0	0	476	0.44	0.44	[0.44,0.44]	0.44	0.44	[0.44,0.44]
(2)	0	0	0	0	0	0	1	0	0	126	0.46	0.48	[0.47,0.48]	0.46	0.48	[0.47,0.48]
(3)	0	0	0	0	0	1	0	0	0	227	0.48	0.47	[0.46,0.47]	0.48	0.47	[0.46,0.47]
(4)	0	0	0	0	0	1	1	0	0	146	0.47	0.45	[0.44,0.45]	0.47	0.45	[0.44,0.45]
(5)	0	0	0	0	1	0	0	?	0	28	0.23	0.24	[0.24,0.25]	0.23	0.24	[0.24,0.25]
(6)	0	0	0	0	1	0	1	?	0	7	0.47	0.56	[0.54,0.58]	0.47	0.56	[0.54,0.58]
(7)	0	0	0	0	1	1	0	?	0	26	0.66	0.58	[0.57,0.59]	0.66	0.58	[0.57,0.59]
(8)	0	0	0	0	1	1	1	?	0	15	0.70	0.75	[0.74,0.77]	0.70	0.75	[0.74,0.77]
(9)	0	0	0	1	0	0	0	0	0	188	0.50	0.49	[0.48,0.49]	0.50	0.49	[0.48,0.49]
(10)	0	0	0	1	0	0	1	0	0	118	0.41	0.41	[0.41,0.42]	0.41	0.41	[0.41,0.42]
(11)	0	0	0	1	0	1	0	0	0	60	0.51	0.53	[0.53,0.54]	0.51	0.53	[0.53,0.54]
(12)	0	0	0	1	0	1	1	0	0	65	0.39	0.39	[0.39,0.40]	0.39	0.39	[0.39,0.40]
(13)	0	0	0	1	1	0	0	?	0	17	0.40	0.53	[0.51,0.55]	0.40	0.53	[0.51,0.55]
(14)	0	0	0	1	1	0	1	?	?	4	0.25	0.33	[0.31,0.35]	0.25	0.33	[0.31,0.35]
(15)	0	0	0	1	1	1	0	?	0	6	0.74	0.75	[0.73,0.76]	0.74	0.75	[0.73,0.76]
(16)	0	0	0	1	1	1	1	?	?	3	0.83	0.76	[0.74,0.78]	0.83	0.76	[0.74,0.78]
(17)	0	0	1	0	0	0	0	0	0	143	0.36	0.40	[0.40,0.41]	0.36	0.40	[0.40,0.41]
(18)	0	0	1	0	0	0	1	?	0	14	0.40	0.39	[0.38,0.40]	0.40	0.39	[0.38,0.40]
(19)	0	0	1	0	0	1	0	0	0	53	0.49	0.46	[0.45,0.46]	0.49	0.46	[0.45,0.46]
(20)	0	0	1	0	0	1	1	0	0	35	0.50	0.47	[0.46,0.47]	0.50	0.47	[0.46,0.47]
(21)	0	0	1	0	1	0	0	?	?	1	0.05	0.05	[0.05,0.05]	0.05	0.05	[0.05,0.05]
(22)	0	0	1	0	1	0	1	?	?	1	0.00	0.00	[0.00,0.00]	0.00	0.00	[0.00,0.00]
(23)	0	0	1	0	1	1	0	?	?	2	0.25	0.24	[0.22,0.26]	0.25	0.24	[0.22,0.26]
(24)	0	0	1	0	1	1	1	?	?	0	-	0.30	[0.24,0.35]	-	0.30	[0.24,0.35]
(25)	0	0	1	1	0	0	0	0	0	79	0.46	0.45	[0.45,0.46]	0.46	0.45	[0.45,0.46]

(26)	0	0	1	1	0	0	1	0	0	51	0.39	0.43	[0.42,0.43]	0.39	0.43	[0.42,0.43]
(27)	0	0	1	1	0	1	0	?	0	22	0.32	0.34	[0.34,0.35]	0.32	0.34	[0.34,0.35]
(28)	0	0	1	1	0	1	1	0	0	30	0.43	0.42	[0.41,0.43]	0.43	0.42	[0.41,0.43]
(29)	0	0	1	1	1	0	0	?	?	2	0.27	0.37	[0.34,0.41]	0.27	0.37	[0.34,0.41]
(30)	0	0	1	1	1	0	1	?	?	2	0.92	0.87	[0.84,0.90]	0.92	0.87	[0.84,0.90]
(31)	0	0	1	1	1	1	0	?	?	2	0.27	0.39	[0.36,0.42]	0.27	0.39	[0.36,0.42]
(32)	0	0	1	1	1	1	1	?	?	0	-	0.47	[0.38,0.56]	-	0.47	[0.38,0.56]
(33)	0	1	0	0	0	0	0	0	0	191	0.49	0.47	[0.47,0.48]	0.49	0.47	[0.47,0.48]
(34)	0	1	0	0	0	0	1	0	0	32	0.39	0.39	[0.38,0.39]	0.39	0.39	[0.38,0.39]
(35)	0	1	0	0	0	1	0	0	0	111	0.43	0.43	[0.42,0.43]	0.43	0.43	[0.42,0.43]
(36)	0	1	0	0	0	1	1	0	0	106	0.52	0.53	[0.52,0.53]	0.52	0.53	[0.52,0.53]
(37)	0	1	0	0	1	0	0	?	?	4	0.58	0.44	[0.42,0.47]	0.58	0.44	[0.42,0.47]
(38)	0	1	0	0	1	0	1	?	?	1	0.18	0.13	[0.11,0.16]	0.18	0.13	[0.11,0.16]
(39)	0	1	0	0	1	1	0	?	0	11	0.84	0.76	[0.74,0.78]	0.84	0.76	[0.74,0.78]
(40)	0	1	0	0	1	1	1	?	?	2	0.78	0.74	[0.71,0.76]	0.78	0.74	[0.71,0.76]
(41)	0	1	0	1	0	0	0	0	0	158	0.50	0.51	[0.51,0.51]	0.50	0.51	[0.51,0.51]
(42)	0	1	0	1	0	0	1	0	0	121	0.40	0.39	[0.39,0.40]	0.40	0.39	[0.39,0.40]
(43)	0	1	0	1	0	1	0	0	0	52	0.52	0.49	[0.48,0.49]	0.52	0.49	[0.48,0.49]
(44)	0	1	0	1	0	1	1	0	0	101	0.38	0.38	[0.38,0.39]	0.38	0.38	[0.38,0.39]
(45)	0	1	0	1	1	0	0	?	0	9	0.55	0.53	[0.50,0.55]	0.55	0.53	[0.50,0.55]
(46)	0	1	0	1	1	0	1	?	0	5	0.58	0.69	[0.65,0.73]	0.58	0.69	[0.65,0.73]
(47)	0	1	0	1	1	1	0	?	0	13	0.60	0.72	[0.70,0.74]	0.60	0.72	[0.70,0.74]
(48)	0	1	0	1	1	1	1	?	1	21	0.92	0.87	[0.85,0.88]	0.92	0.87	[0.85,0.88]
(49)	0	1	1	0	0	0	0	0	0	60	0.43	0.43	[0.42,0.44]	0.43	0.43	[0.42,0.44]
(50)	0	1	1	0	0	0	1	?	0	12	0.35	0.39	[0.38,0.41]	0.35	0.39	[0.38,0.41]
(51)	0	1	1	0	0	1	0	0	0	32	0.43	0.39	[0.38,0.40]	0.43	0.39	[0.38,0.40]
(52)	0	1	1	0	0	1	1	?	0	23	0.45	0.49	[0.48,0.50]	0.45	0.49	[0.48,0.50]
(53)	0	1	1	0	1	0	0	?	?	1	0.60	0.50	[0.45,0.54]	0.60	0.50	[0.45,0.54]
(54)	0	1	1	0	1	0	1	?	?	0	-		-	-		-
(55)	0	1	1	0	1	1	0	?	?	3	0.78	0.82	[0.79,0.85]	0.78	0.82	[0.79,0.85]

(56)	0	1	1	0	1	1	1	?	?	1	1.00	0.88	[0.86,0.91]	1.00	0.88	[0.86,0.91]
(57)	0	1	1	1	0	0	0	0	0	70	0.52	0.50	[0.50,0.51]	0.52	0.50	[0.50,0.51]
(58)	0	1	1	1	0	0	1	0	0	58	0.45	0.51	[0.50,0.52]	0.45	0.51	[0.50,0.52]
(59)	0	1	1	1	0	1	0	0	0	36	0.37	0.42	[0.41,0.42]	0.37	0.42	[0.41,0.42]
(60)	0	1	1	1	0	1	1	0	0	36	0.39	0.42	[0.42,0.43]	0.39	0.42	[0.42,0.43]
(61)	0	1	1	1	1	0	0	?	?	3	0.54	0.77	[0.74,0.81]	0.54	0.77	[0.74,0.81]
(62)	0	1	1	1	1	0	1	?	?	4	0.87	0.93	[0.90,0.95]	0.87	0.93	[0.90,0.95]
(63)	0	1	1	1	1	1	0	?	?	2	0.59	0.70	[0.67,0.73]	0.59	0.70	[0.67,0.73]
(64)	0	1	1	1	1	1	1	?	1	5	0.89	0.93	[0.91,0.94]	0.89	0.93	[0.91,0.94]
(65)	1	0	0	0	0	0	0	0	0	105	0.55	0.56	[0.56,0.57]	0.55	0.56	[0.56,0.57]
(66)	1	0	0	0	0	0	1	0	0	112	0.51	0.53	[0.53,0.54]	0.51	0.53	[0.53,0.54]
(67)	1	0	0	0	0	1	0	0	0	160	0.66	0.68	[0.67,0.68]	0.66	0.68	[0.67,0.68]
(68)	1	0	0	0	0	1	1	0	0	265	0.62	0.61	[0.60,0.61]	0.62	0.61	[0.60,0.61]
(69)	1	0	0	0	1	0	0	?	0	7	0.60	0.61	[0.59,0.63]	0.60	0.61	[0.59,0.63]
(70)	1	0	0	0	1	0	1	?	?	4	0.43	0.64	[0.62,0.66]	0.43	0.64	[0.62,0.66]
(71)	1	0	0	0	1	1	0	?	0	16	0.69	0.71	[0.70,0.72]	0.69	0.71	[0.70,0.72]
(72)	1	0	0	0	1	1	1	1	1	36	0.79	0.82	[0.80,0.83]	0.79	0.82	[0.80,0.83]
(73)	1	0	0	1	0	0	0	0	0	145	0.57	0.59	[0.58,0.59]	0.57	0.59	[0.58,0.59]
(74)	1	0	0	1	0	0	1	0	0	200	0.49	0.50	[0.50,0.50]	0.49	0.50	[0.50,0.50]
(75)	1	0	0	1	0	1	0	0	0	67	0.58	0.62	[0.61,0.62]	0.58	0.62	[0.61,0.62]
(76)	1	0	0	1	0	1	1	0	0	182	0.57	0.58	[0.57,0.58]	0.57	0.58	[0.57,0.58]
(77)	1	0	0	1	1	0	0	?	0	10	0.59	0.60	[0.58,0.61]	0.59	0.60	[0.58,0.61]
(78)	1	0	0	1	1	0	1	?	0	6	0.65	0.63	[0.62,0.65]	0.65	0.63	[0.62,0.65]
(79)	1	0	0	1	1	1	0	?	1	9	0.81	0.80	[0.79,0.82]	0.81	0.80	[0.79,0.82]
(80)	1	0	0	1	1	1	1	?	0	17	0.69	0.71	[0.69,0.73]	0.69	0.71	[0.69,0.73]
(81)	1	0	1	0	0	0	0	?	0	17	0.40	0.41	[0.40,0.42]	0.40	0.41	[0.40,0.42]
(82)	1	0	1	0	0	0	1	?	0	17	0.38	0.40	[0.39,0.41]	0.38	0.40	[0.39,0.41]
(83)	1	0	1	0	0	1	0	0	0	44	0.72	0.69	[0.68,0.70]	0.72	0.69	[0.68,0.70]
(84)	1	0	1	0	0	1	1	0	0	40	0.50	0.54	[0.53,0.55]	0.50	0.54	[0.53,0.55]
(85)	1	0	1	0	1	0	0	?	?	0	-	0.41	[0.38,0.44]	-	0.41	[0.38,0.44]

(86)	1	0	1	0	1	0	1	?	?	0	-	0.00	[0.00,0.00]	-	0.00	[0.00,0.00]
(87)	1	0	1	0	1	1	0	?	?	2	0.00	0.00	[0.00,0.00]	0.00	0.00	[0.00,0.00]
(88)	1	0	1	0	1	1	1	?	?	0	-	0.33	[0.30,0.36]	-	0.33	[0.30,0.36]
(89)	1	0	1	1	0	0	0	0	0	53	0.47	0.51	[0.50,0.51]	0.47	0.51	[0.50,0.51]
(90)	1	0	1	1	0	0	1	0	0	63	0.45	0.44	[0.43,0.44]	0.45	0.44	[0.43,0.44]
(91)	1	0	1	1	0	1	0	?	0	24	0.56	0.56	[0.55,0.57]	0.56	0.56	[0.55,0.57]
(92)	1	0	1	1	0	1	1	0	0	52	0.40	0.39	[0.39,0.40]	0.40	0.39	[0.39,0.40]
(93)	1	0	1	1	1	0	0	?	?	4	0.66	0.72	[0.69,0.75]	0.66	0.72	[0.69,0.75]
(94)	1	0	1	1	1	0	1	?	?	1	0.84	0.73	[0.70,0.76]	0.84	0.73	[0.70,0.76]
(95)	1	0	1	1	1	1	0	?	?	0	-	0.11	[0.10,0.13]	-	0.11	[0.10,0.13]
(96)	1	0	1	1	1	1	1	?	?	4	0.99	0.65	[0.62,0.68]	0.99	0.65	[0.62,0.68]
(97)	1	1	0	0	0	0	0	0	0	35	0.53	0.53	[0.52,0.53]	0.53	0.53	[0.52,0.53]
(98)	1	1	0	0	0	0	1	0	0	37	0.44	0.47	[0.46,0.48]	0.44	0.47	[0.46,0.48]
(99)	1	1	0	0	0	1	0	0	0	48	0.55	0.58	[0.57,0.58]	0.55	0.58	[0.57,0.58]
(100)	1	1	0	0	0	1	1	0	0	131	0.56	0.58	[0.58,0.59]	0.56	0.58	[0.58,0.59]
(101)	1	1	0	0	1	0	0	?	?	1	0.57	0.59	[0.55,0.63]	0.57	0.59	[0.55,0.63]
(102)	1	1	0	0	1	0	1	?	?	0	-	0.26	[0.23,0.29]	-	0.26	[0.23,0.29]
(103)	1	1	0	0	1	1	0	?	0	5	0.47	0.68	[0.64,0.71]	0.47	0.68	[0.64,0.71]
(104)	1	1	0	0	1	1	1	?	?	1	0.18	0.14	[0.12,0.15]	0.18	0.14	[0.12,0.15]
(105)	1	1	0	1	0	0	0	0	0	76	0.60	0.59	[0.58,0.59]	0.60	0.59	[0.58,0.59]
(106)	1	1	0	1	0	0	1	0	0	182	0.46	0.46	[0.46,0.47]	0.46	0.46	[0.46,0.47]
(107)	1	1	0	1	0	1	0	0	0	32	0.60	0.55	[0.54,0.55]	0.60	0.55	[0.54,0.55]
(108)	1	1	0	1	0	1	1	0	0	196	0.48	0.47	[0.47,0.48]	0.48	0.47	[0.47,0.48]
(109)	1	1	0	1	1	0	0	?	?	4	0.82	0.73	[0.71,0.76]	0.82	0.73	[0.71,0.76]
(110)	1	1	0	1	1	0	1	?	0	12	0.75	0.76	[0.74,0.78]	0.75	0.76	[0.74,0.78]
(111)	1	1	0	1	1	1	0	?	?	2	0.78	0.80	[0.78,0.83]	0.78	0.80	[0.78,0.83]
(112)	1	1	0	1	1	1	1	?	0	5	0.27	0.27	[0.25,0.28]	0.27	0.27	[0.25,0.28]
(113)	1	1	1	0	0	0	0	?	0	23	0.51	0.54	[0.53,0.56]	0.51	0.54	[0.53,0.56]
(114)	1	1	1	0	0	0	1	?	0	8	0.49	0.54	[0.53,0.55]	0.49	0.54	[0.53,0.55]
(115)	1	1	1	0	0	1	0	?	1	27	0.83	0.77	[0.76,0.78]	0.83	0.77	[0.76,0.78]

(116)	1	1	1	0	0	1	1	0	0	32	0.47	0.54	[0.53,0.56]	0.47	0.54	[0.53,0.56]
(117)	1	1	1	0	1	0	0	?	?	1	0.96	0.90	[0.87,0.92]	0.96	0.90	[0.87,0.92]
(118)	1	1	1	0	1	0	1	?	?	0	-	0.00	[0.00,0.00]	-	0.00	[0.00,0.00]
(119)	1	1	1	0	1	1	0	?	?	0	-	0.54	[0.11,0.96]	-	0.54	[0.11,0.96]
(120)	1	1	1	0	1	1	1	?	?	0	-	0.45	-	-	0.45	-
(121)	1	1	1	1	0	0	0	0	0	63	0.58	0.61	[0.60,0.61]	0.58	0.61	[0.60,0.61]
(122)	1	1	1	1	0	0	1	0	0	80	0.57	0.55	[0.54,0.55]	0.57	0.55	[0.54,0.55]
(123)	1	1	1	1	0	1	0	?	0	24	0.63	0.63	[0.62,0.64]	0.63	0.63	[0.62,0.64]
(124)	1	1	1	1	0	1	1	0	0	91	0.51	0.54	[0.54,0.55]	0.51	0.54	[0.54,0.55]
(125)	1	1	1	1	1	0	0	?	?	4	0.64	0.76	[0.72,0.80]	0.64	0.76	[0.72,0.80]
(126)	1	1	1	1	1	0	1	?	?	3	0.99	0.68	[0.63,0.73]	0.99	0.68	[0.63,0.73]
(127)	1	1	1	1	1	1	0	?	?	1	0.64	0.57	[0.55,0.60]	0.64	0.57	[0.55,0.60]
(128)	1	1	1	1	1	1	1	?	?	2	0.99	0.67	[0.63,0.71]	0.99	0.67	[0.63,0.71]

Appendix 4.2: Calibration Thresholds for the Robustness Tests

Outcome[46]	**Calibration Threshold(s)**
Innovation Impact (IMPACT_INNO)	Fuzzy calibration[47]: e: 5th percentile (poor outcomes) c: 50th percentile i: 95th percentile (highly impactful outcomes)
Condition	**Calibration Threshold(s)**
Knowledge Dissimilarity (KNOW_DIS)	Inverse-U-shaped fuzzy calibration: e1: 10th percentile c1: 20th percentile i1: 40rd percentile i2: 60th percentile c2: 80th percentile e2: 90th percentile Fuzzy calibration: e: 10th percentile c: 50th percentile i: 90th percentile
Ethnic Diversity (ETHN)	Fuzzy calibration: e: 0 (no ethnic diversity) c: 0.25 (moderate diversity) i: 0.80 (significant diversity)
Gender Diversity (GEND)	Fuzzy calibration: e: 0 (male / female only team) c: 0.25 (moderate diversity) i: 0.45 (significant diversity)
Institutional Diversity (INST)	Fuzzy calibration: e: 0 c: 75th percentile i: 90th percentile
Domain Experience (DOM)	Crisp calibration[48]: c: > 1 (on average, each team member has filed a patent in the same domain in the past)
Degree Centrality (DEG)	Fuzzy calibration: e: 0 (no outside collaborations) c: 50th percentile i: 90th percentile
Prior Collaboration (PRICOL)	Fuzzy calibration: e: 0 (no prior collaboration) c: 1.5 (members have worked with each other one and a half times on average) i: 3 (members have worked with each other three times on average)
Inventor Mobility (MOB)	Fuzzy calibration: e: 10th percentile c: 50th percentile i: 90th percentile
Recombination Novelty (RECOMB)	Fuzzy calibration: e: 0.1 (mainly familiar combinations, exploitation) c: 0.5 (half the combinations are novel to the team) i: 1 (only unfamiliar combinations, exploration)

[46] Robustness tests with the recalibrated outcome were conducted using the initial calibrations for the causal conditions from Table 3.1.
[47] Although technically applying a fuzzy calibration here, I only use full members and full non-members to create more contrast in the outcome. Therefore, this can also be viewed as a crisp calibration with two thresholds.
[48] The data distribution is highly skewed with most cases exhibiting no domain experience. I therefore maintain a crisp calibration.

Appendix 4.3: Configuration Chart for Impactful Innovations with Substituted Conditions and Condition Calibrations for Robustness Tests.

	Common Configurations	Including Rare Configurations			
	(1a)	(1b)	(1c)	(2)	(3)
Institutional Diversity	●		●		
Ethnic Diversity	⊗	⊗	⊗	●	●
Gender Diversity	⊗	⊗	⊗	⊗	
Knowledge Dissimilarity (∫)	⊗		⊗		●
Domain Experience	⬤	●	●	●	●
Prior Collaboration	⬤	●	●	●	●
Mobile Inventors	●	●		⊗	●
Consistency	0.85	0.82	0.85	0.83	0.87
Raw Coverage	0.006	0.012	0.011	0.007	0.006
Unique Coverage	-	0.005	0.002	0.004	0.006
Overall Model Consistency	**0.79**	**0.83**			
Overall Model Coverage	**0.008**	**0.026**			

Note: Knowledge dissimilarity has a logistic calibration curve. Also, for both frequency cutoffs, alternate solutions emerge (model ambiguity), depending on the choice of prime implicants. However, all alternate solutions have significantly lower model performance (w.r.t. consistency and coverage) and are, thus, not reported.

Appendix 4.4: Supplemental Online Appendix

I provide the truth tables for the analysis of the absence of the outcome (i.e., non-impactful innovations) as well as the truth tables for the robustness tests in an online appendix. For access, contact *niklas.hagenow(at)tum.de*.

Contributions and Supplemental Aids

Contributions Chapter 2

I developed the idea of the literature review presented in this chapter in collaboration with my supervisor and co-author Siddharth Vedula as well as my co-author Claudia Doblinger. I developed the conceptual approach to this chapter and wrote this chapter myself, while incorporating comments made by my co-authors over multiple iterations on the manuscript. Susanne Kurowski, as additional co-author, supported the process by reviewing the selection of articles based on a random selection of a portion of the articles to be included or excluded.

Co-authors: Siddharth Vedula, Claudia Doblinger, Susanne Kurowski

Contributions Chapter 3

I elaborated an earlier version of the methodological approach introduced in this chapter in collaboration with my supervisor and co-author Siddharth Vedula. The initial approach was based on using feature importance values resulting from a random forest analysis to identify the most influential conditions in a data-driven way. After discarding that approach, I revised some of the initial ideas and developed the cluster-based method by myself. Using solution consistency and coverage to compare the performance of different model specifications was discussed with Peer Fiss (University of Southern California) during a QCA Paper Development Workshop at the Antwerp Management School in December 2023. The chapter was written by myself and revised based on comments by my supervisor.

Co-authors: Siddharth Vedula

Contributions Chapter 4

The idea and conceptual approach for the QCA study presented in this chapter was developed in collaboration with my supervisor and co-author Siddharth Vedula as well as my co-author Claudia Doblinger. The manuscript was written by myself and revised in multiple iterations based on comments made by my co-authors and valuable feedback received during the DRUID22 conference in Copenhagen, the EGOS24 conference in Milan, as well as QCA Paper Development Workshops in Zurich (December 2022) and Antwerp (December 2023). Scholars providing comments on earlier stages of this chapter include Peer Fiss (University of Southern California), Adrian Dușa (University of Bucharest), Roel Rutten (Tilburg University), Christian Rupietta (Queen's University Belfast), and Petteri Leppänen (IE University).

Co-authors: Siddharth Vedula, Claudia Doblinger

Supplemental Aids

I used AI tools (e.g., ChatGPT) to revise the form and language of my writing. All sections were written by me and were merely revised using AI tools to correct spelling and punctuation and to enhance the sentence structure and wording to improve the overall reading flow where advisable. Suggestions were only included after a thorough assessment by myself. Furthermore, I used AI to aid and revise my coding in Python and R. For computationally intense tasks, I had access to cloud computing resources provided by the *Leibniz Rechenzentrum (LRZ)*.