Delft University of Technology

Master Thesis - Management of Technology

"The Impact of Corporate Dominance, Geographic Proximity, and Technological Proximity on consortia Success"

Author: Fabian Ruby Michaël Roumans

Faculty Technology, Policy and Management
Student number: 5602238
Email address: froumans@student.tudelft.nl

Chair: Geerten van de Kaa
First supervisor: Sander Smit
Second supervisor: Ibo van de Poel

August 14, 2024

Abstract

This thesis examines the interactions within standard-setting consortia within the Audio/Video/Multimedia sector, focusing on large company dominance, geographical proximity, and technological proximity. It aims to uncover how these factors individually and collectively influence the success of these consortia. The guiding research question is: "What combinations of large company dominance, geographic proximity, and technological proximity lead to successful outcomes in standard-setting consortia?"

Using Qualitative Comparative Analysis (QCA), the study reveals that successful consortia strike a balance in large company influence, maintain significant geographical proximity, and ensure proper technological alignment. While large company dominance significantly impacts consortium success, an optimal balance is essential to avoid power struggles and foster effective collaboration. Geographical proximity, especially at the UN subregion level, consistently contributes to success by enhancing trust and communication. Technological proximity within industry groups is beneficial but must be complemented by other factors to significantly impact outcomes. It's clear that the success of consortia is best understood through specific configurations of these variables rather than any single factor alone.

To evaluate consortium success, the study employs a multifactor framework focusing on the creation of standards, their adoption, and scholarly recognition. This framework combines qualitative and quantitative measures, providing a comprehensive assessment of consortium performance.

The research makes a valuable contribution to the field by offering empirical evidence on the strategic influence of large companies within standard-setting consortia. It extends the understanding of how large firms drive innovation while balancing the contributions of smaller participants. The study also offers nuanced insights into the roles of geographical and technological proximities, emphasizing their combined effects on consortium success. These findings are useful for both theoretical knowledge and practical applications, informing technology management practices and shaping policies that support effective standard-setting efforts.

From a Management of Technology perspective, this thesis demonstrates how strategic engagement in standard-setting consortia can enhance a firm's technological capabilities and market positioning. Technology managers can leverage these insights to navigate standard-setting processes more effectively, ensuring that their firms benefit from collaboration while maintaining an optimal balance of influence.

However, this study acknowledges certain practical limitations. The findings, while insightful for the Audio/Video/Multimedia sector, may need adaptation when applied to other industries with different dynamics. Additionally, the reliance on publicly available data from consortium websites and LinkedIn profiles may lead to practical challenges, such as gaps or inconsistencies in the data, affecting decision-making. The study's cross-sectional approach provides a snapshot of current conditions but does not capture consortium dynamics over time. Practitioners should consider these factors when applying the insights to other contexts, and future research should aim to include a wider range of industries and explore these dynamics longitudinally to inform more adaptive strategies.

Contents

List of abbreviation

Abbreviation	Full Form	Explanation
QCA	Qualitative Comparative Analysis	A research method used for comparing qualitative data by converting it into sets for systematic comparison.
CDS	Consortium Dominance Score	A metric used to measure the dominance of large companies within a consortium.
FIPS	Federal Information Processing Standards	Standards developed by the US federal government for computer systems.
NUTS	Nomenclature of Territorial Units for Statistics	A hierarchical system for dividing up the economic territory of the EU.
SME	Small and Medium-sized Enterprises	Businesses with a small to medium number of employees and turnover.
UN	United Nations	An international organization founded to promote peace, security, and cooperation among countries.
GIS	Geographic Information Systems	Systems designed to capture, store, manipulate, analyze, manage, and present spatial or geographic data.
ICT	Information and Communication Technology	An extensional term for information technology that stresses the role of unified communications and the integration of telecommunications.
IEEE	Institute of Electrical and Electronics Engineers	A professional association dedicated to advancing technology for the benefit of humanity.
fsQCA	Fuzzy Set Qualitative Comparative Analysis	An extension of QCA that allows for the analysis of sets with varying degrees of membership, not just binary presence or absence.
MSCI	Morgan Stanley Capital International	A global provider of equity, fixed income, hedge fund stock market indexes, and equity portfolio analysis tools.
R&D	Research and Development	Activities in connection with corporate or governmental innovation and introduction of new products and services.
SSC	Standard Setting Consortia	Groups formed by various organizations to develop and implement standards in a specific industry or field.

1 Introduction

1.1 Background

In an era where technological convergence is the norm, standards have become the cornerstones of innovation and interoperability in the global technological landscape. Standards are not just technical product specifications but rather are the rules that ensure that hardware and software from different sources work together seamlessly, driving the industry forward (Ray & Jones, 2003). In this context, Standard Setting Consortia (SSCs) have emerged as vital platforms where industry stakeholders work together to develop these essential standards. The formation of such consortia underscores the essential role of collaboration in advancing technological advances and setting industry standards. These consortia bring together different entities to discuss, negotiate, and ultimately create new standards (Katz & Martin, 1997). The composition of these consortia varies from case to case, involving a mix of multinational corporations, smaller companies, and academic institutions. Collaboration within them attests to the industry's understanding that no single entity holds all the cards for innovation. Through joint effort and shared vision consortia make it possible that technological frontiers can be pushed (Hagedoorn, Link, & Vonortas, 2000).

The critical role of consortia in technological development is increasingly recognized as industries become more interconnected and reliant on common standards to ensure compatibility and interoperability. Consortia serve as forums where stakeholders from different sectors, including corporations, government entities, and academic institutions, collaborate to develop standards that facilitate technological innovation and economic growth. The emergence of consortia reflects broader trends in industrial collaboration and innovation, underscoring the importance of collective action in addressing complex technological challenges.

Studies have shown that the composition and structure of consortia significantly impact their effectiveness and the quality of the standards they produce. For example, research by Choi, Raghu, Vinzé, and Dooley (2019) and Teubner, Henkel, and Bekkers (2021) highlights the necessity for varied participation in e-business standards, emphasizing the distinct roles of IT vendors and users in the standard-setting process. Similarly, Fukami and Shimizu (2021) provide insights into strategic maneuvers within consortia, showcasing how large corporations leverage both formal and informal networks to influence standard-setting outcomes.

1.2 Problem statement

The dynamics within standard-setting consortia (SSCs) are complex and shaped by the interaction of different actors, each with their own agenda and level of influence. Large companies, with their extensive resources and market reach, often become central players in these consortia, steering discussions and decisions in directions that align with their strategic interests(Lemley, 2002; Simcoe, 2012). While the influence of these major players is significant, the success of a consortium relies on the inclusiveness and equitable participation of all members to ensure that the standards developed are comprehensive, innovative, and widely accepted(Baron & Pohlmann, 2013).

However, the dominance of large corporations in SSCs can lead to an imbalance, where the interests of smaller players and the broader industry may be overlooked. This dominance can result in standards skewed towards the proprietary interests of the dominant firms, rather than reflecting the wider needs of the industry, potentially stifling innovation and limiting diverse perspectives. The strategic positioning of these corporations within SSCs often involves leveraging both formal and informal networks to exert influence, further entrenching their dominance and complicating efforts to achieve inclusive and equitable standard-setting processes.

Geographical and technological proximity among consortium members further complicate these dynamics. Geographical proximity facilitates face-to-face interactions, trust-building, and easier knowledge exchange, which are essential for innovation. However, it can also lead to a homogeneity of ideas and an echo chamber effect, limiting the diversity of knowledge and perspectives. Technological proximity, referring to the extent to which consortium members share similar knowledge bases and cognitive frameworks, improves communication efficiency and mutual understanding. Yet, excessive cognitive similarity can stifle new perspectives and ideas, potentially hindering innovation.

In conclusion, while large companies play a crucial role in standard-setting consortia due to their resources and influence, it is imperative to foster an inclusive and diverse environment. Balancing the contributions of all members, along with managing the effects of geographical and technological proximity, is essential for developing standards that are not only innovative but also representative of the entire industry's needs.

1.3 Research objective

This thesis aims to investigate the combinations of large company dominance, geographic proximity, and technological proximity that lead to successful outcomes in standard-setting consortia. By examining how these factors individually and collectively influence the efficacy and success of standards, this research seeks to provide a balanced perspective on the positive and negative consequences of corporate dominance in standardization. The insights gained may inform policies and strategies to enhance the collaborative and innovative potential of technology and corporate standardization efforts.

1.4 Research question

The primary research question guiding this study is: **"What combinations of large company dominance, geographic proximity, and technological proximity lead to successful outcomes in standard-setting consortia?"**

This question aims to address the unresolved gap in understanding how the interplay of these factors impacts the effectiveness and success of standards development. The study explores how the dominance of large companies within consortia can shape the standard-setting process, potentially steering outcomes to favor their strategic interests. It also investigates the role of geographic proximity, considering how the physical closeness of consortium members can facilitate collaboration, trust-building, and knowledge exchange, while also potentially leading to homogeneity of ideas. Additionally, the research delves into technological proximity, examining how shared knowledge bases and cognitive frameworks among consortium members can influence the innovation and success of the standards developed. By analyzing these factors and their interconnections, this study seeks to provide a comprehensive understanding of the conditions that foster effective and successful standard-setting consortia.

1.5 Structure

This thesis is structured to systematically explore and answer the research question. Each chapter of this thesis contributes to answering this question by addressing specific aspects of the study.

Chapter 1: Introduction establishes the foundation for the research. It presents the background of the study, the problem statement, and the research objective, all of which are crucial for understanding the context and significance of the research question. This chapter also outlines the scope of the study, defining the boundaries within which the research is conducted.

Chapter 2: Literature Review and Theoretical Framework builds the theoretical framework necessary to tackle the research question. By reviewing the existing body of knowledge on standard-setting consortia, this chapter identifies key concepts, theories, and gaps in the current research. This literature review sets the stage for the analytical approach used in the study and helps refine the research question.

Chapter 3: Research Methodology describes the research design and the methodological steps taken to answer the research question. It details the use of the Qualitative Comparative Analysis (QCA) approach, explaining the rationale for its selection, the process of case selection, data collection, and the calibration of data. This chapter demonstrates how QCA is employed to systematically compare cases and identify patterns of conditions that contribute to successful outcomes in standard-setting consortia.

Chapter 4: Results presents the findings from the QCA. It includes the calibrated data, truth tables, and an analysis of the necessary and sufficient conditions for successful consortium outcomes. This chapter directly addresses the research question by providing a detailed examination of how large company dominance, geographic proximity, and technological proximity influence the success of standard-setting processes.

Chapter 5: Discussion interprets the results in light of the existing literature and theoretical framework. It explores the implications of the findings for both theory and practice, discussing how the identified patterns contribute to a deeper understanding of standard-setting consortia. This chapter also critically assesses the limitations of the study and suggests directions for future research, which are essential for refining the conclusions drawn from the research.

Chapter 6: Conclusion synthesizes the insights gained throughout the thesis, offering a final answer to the research question. It emphasizes the contributions of the study to the field of standardization and provides concluding remarks on the influence of large company dominance, geographic proximity, and technological proximity on the success of standard-setting consortia.

The thesis concludes with a comprehensive list of References, documenting all the academic sources and materials cited throughout the report. The Appendices include supplementary materials such as the calibrated dataset, truth tables, and additional methodological details, ensuring transparency and facilitating further exploration of the study's findings.

2 Literature Review and Theoretical Framework

This chapter explores the landscape of consortia, including their organizational structure, the roles of participating entities, and the critical factors that influence their success. By examining various combinations of conditions within consortia, this chapter seeks to understand how these configurations contribute to successful outcomes, particularly in technology and innovation sectors. The discussion integrates key concepts from the literature with relevant theoretical frameworks to provide a comprehensive understanding of how different elements interact to shape consortium dynamics.

2.1 Landscape and Organization of Consortia

Definition and Structure of Consortia

Consortia are collaborative alliances formed by multiple organizations that come together to achieve objectives that surpass the capabilities of individual members. These alliances are particularly significant in sectors such as technology and innovation, where the development of new standards and technologies requires substantial resources, specialized expertise, and collective effort. According to Baron, Ménière, and Pohlmann (2014), consortia facilitate the pooling of resources and knowledge, enabling faster innovation and the more efficient implementation of industry standards. Unlike more formalized entities such as Standard Setting Organizations (SSOs), consortia are often characterized by their flexibility, inclusivity, and speed in decision-making, which are critical in dynamic sectors where rapid responses to market and technological changes are necessary. This flexibility allows a broader range of stakeholders, including smaller firms, to participate actively and contribute meaningfully to the consortium's objectives.

The organizational structure of consortia typically involves a complex interplay of resources, capabilities, and strategic interests among the participating entities. This structure not only impacts the effectiveness of collaboration within the consortium but also its ability to adapt to evolving market conditions and technological advancements. As highlighted by Baron et al. (2014), the dynamic nature of consortia is pivotal in accelerating the development and implementation of industry standards, reducing research and development coordination failures, and fostering innovation across various sectors.

While consortia share similarities with other forms of collaboration, such as joint ventures and strategic alliances, they are distinguished by their collective approach to setting industry standards and driving innovation. Joint ventures typically involve a more formalized and often equity-based partnership focused on specific business objectives, whereas strategic alliances might not require equity sharing but still involve coordinated efforts toward common goals. Consortia, however, are unique in their emphasis on collaborative innovation and standard-setting, often bringing together a diverse group of stakeholders who may not have direct financial stakes in each other's businesses but share a vested interest in the success of the consortium's objectives (Eisenhardt & Schoonhoven, 1996).

Roles and Disciplines Involved

The success of a consortium is significantly influenced by the diversity of disciplines and expertise brought together by its members. Participants from various fields such as engineering, software development, regulatory compliance, and market analysis collaborate to tackle complex challenges that require a multidisciplinary approach. Leiponen (2008) emphasizes that this diversity of expertise allows consortia to address technological and innovative challenges more comprehensively, as the combination of different areas of knowledge leads to more effective problem-solving and innovative outcomes.

In a consortium, the roles of participating entities are often defined by their core competencies and strategic interests. For instance, large technology firms may contribute their advanced research capabilities and extensive market reach, while smaller firms or startups might bring niche expertise and innovative approaches that larger firms lack. Regulatory experts ensure that the innovations comply with industry standards and legal requirements, while market analysts provide insights into consumer behavior and market trends, ensuring that the consortium's innovations are both viable and market-ready. This multidisciplinary collaboration is essential for addressing the complexities of technology and innovation holistically, allowing consortia to create solutions that are not only technically sound but also commercially successful (Schilling & Phelps, 2007).

Furthermore, the interaction of these diverse disciplines within a consortium fosters an environment where knowledge is not just shared but also synthesized into new ideas and innovations. For example, engineers and software developers working closely with regulatory experts can anticipate and integrate compliance requirements into the design and development stages of technology projects, thereby reducing time-to-market and avoiding costly redesigns. Similarly, by incorporating market analysis early in the innovation process, consortia can better align their technological developments with market needs, increasing the likelihood of commercial success (Kogut, 1989).

Governance and Decision-Making in Consortia

Governance within consortia is a critical factor that determines their effectiveness and longevity. The governance structure typically involves shared decision-making processes, which are designed to ensure that all participating entities have a voice in the direction and outcomes of the consortium. However, the governance of consortia can vary significantly depending on the size and diversity of the members involved, the objectives of the consortium, and the industry in which it operates (Ring & Ven, 1992).

In some cases, consortia adopt a more hierarchical structure where decision-making power is concentrated among a few key players, often the largest and most resource-rich firms. While this can lead to more streamlined decision-making processes, it also risks marginalizing smaller members and reducing the diversity of ideas that are crucial for innovation. To mitigate these risks, many consortia employ a more inclusive governance model that balances the power dynamics between large and small members, ensuring that decisions are made through consensus and that all members feel their contributions are valued (Freeman, Dmytriyev, & Phillips, 2021).

The flexibility and adaptability of the governance structure are also important. As consortia evolve, their objectives, membership, and external environment may change, necessitating adjustments in how they are governed. Effective consortia often have mechanisms in place for revising their governance structures in response to these changes, allowing them to remain agile and responsive to new challenges and opportunities(Gulati, 1998).

Challenges and Strategies for Effective Collaboration

Consortia present substantial opportunities for fostering innovation through collective efforts, yet they also face significant challenges that can impact their effectiveness. These challenges primarily stem from the complexities of coordinating a diverse array of organizations, each with its own strategic objectives, resources, and operational cultures. The ability to align these diverse elements is crucial for the consortium's success, particularly in dynamic sectors where rapid innovation and adaptability are necessary.

One significant challenge is the dominance of large companies within consortia. While large corporations can provide substantial resources, advanced technologies, and market influence, their dominance can lead to power imbalances. This can skew decision-making processes in favor of their strategic interests, potentially marginalizing smaller members and stifling the diversity of ideas that is critical for innovation. The alignment of strategic interests among consortium members becomes even more complex under these circumstances. Conflicts may arise, particularly regarding the direction of the consortium's initiatives and the allocation of resources, as larger firms might push for outcomes that serve their own goals rather than the collective objectives of the consortium. Establishing clear, shared objectives and maintaining open channels of communication are essential strategies for mitigating these conflicts and ensuring that all members, regardless of size, have a meaningful role in shaping the consortium's direction (Baron et al., 2014).

In addition to power dynamics, managing diversity within consortia is another critical challenge. The variety of expertise, organizational cultures, and operational practices among members can drive innovation but also create friction, particularly when differences in decision-making processes and risk tolerance emerge. Effective consortia must implement strategies that promote mutual understanding and cooperation, such as standardized communication protocols and a collaborative culture (Leiponen, 2008).

A critical aspect of managing this diversity is the concept of proximity, which plays a pivotal role in shaping the interactions within a consortium. Proximity encompasses multiple dimensions, including geographic, technological, and organizational proximity, each of which can significantly influence the effectiveness of collaboration. Geographic proximity refers to the physical closeness of consortium members, which can facilitate more frequent and informal interactions, foster trust, and enhance the efficiency of knowledge exchange. However, geographic proximity also carries the risk of creating echo chambers, where a lack of diversity in ideas and perspectives can stifle innovation (Letaifa & Rabeau, 2013; Porter, 1998).

Technological proximity, or cognitive proximity, pertains to the similarity in knowledge bases and expertise among consortium members. While such proximity can streamline communication and foster mutual understanding, there is a potential downside: excessive similarity may limit the diversity of ideas, which is crucial for driving innovation (Hansen & Mattes, 2018). On the other hand, organizational proximity, defined by shared corporate cultures and aligned goals, further influences how effectively these diverse entities can collaborate. Proximity, therefore, plays a crucial role in either amplifying or mitigating the challenges posed by diversity within consortia, making it a key factor in the overall success of collaborative efforts.

The governance structure of a consortium is equally critical in addressing these challenges. A well-designed governance framework ensures inclusive decision-making, giving all members, regardless of size or influence, a voice in shaping the consortium's direction. Such inclusivity is vital for maintaining the engagement of all members, particularly smaller entities that might otherwise feel overshadowed by larger, more influential organizations. Flexibility in governance is also essential, allowing the consortium to adapt to changing circumstances and evolving member needs (Freeman et al., 2021). This adaptability is particularly important given the dynamic nature of the sectors in which consortia operate. Consortia must be able to pivot quickly in response to technological developments, regulatory changes, or market shifts. A flexible governance structure, coupled with a culture of continuous learning and adaptation, is vital for maintaining resilience and fostering innovation in these uncertain environments (Gulati, 1998).

While consortia are powerful vehicles for innovation and standard-setting, their success depends on effectively managing a complex interplay of factors. By strategically aligning key elements such as member proximity, governance structures, and power play, consortia can better navigate the challenges they face. This strategic alignment is crucial not only for enhancing collaborative outcomes but also for ensuring that the consortium's collective goals are achieved. The following sections will delve deeper into these factors, exploring how specific configurations of these elements influence the overall success of consortia, particularly in terms of innovation and standard-setting.

2.2 State of the Art in Consortia Research

Having established the fundamental structure, roles, and governance of consortia, it is now essential to explore how these elements manifest in contemporary research, particularly in understanding the strategies and impacts of various stakeholders within these collaborative networks. A critical aspect that influences these dynamics is the concept of proximity, which encompasses geographic, technological, and organizational dimensions. Understanding how proximity affects collaboration and innovation within consortia is crucial for comprehending the broader strategic interactions among members, including large corporations.

Choi et al. (2019) and Teubner et al. (2021) provide foundational insights into the complex dynamics of standards consortia, underscoring the roles of diverse stakeholders, including large corporations.Choi et al. (2019) emphasize the necessity for varied participation in e-business standards, particularly highlighting the distinct roles of IT vendors and users. Teubner et al. (2021) expand on this by exploring the diverse motives behind firms' involvement in consortia and their interaction with formal standard setting organizations. Together, these studies reveal a nuanced ecosystem of standard-setting. However, they also surface a critical gap in comprehensively understanding how large corporations leverage their roles to exert influence within these bodies and shape the standard-setting process, potentially influenced by varying degrees of proximity among stakeholders.

Building on this foundation, Fukami and Shimizu (2021) delve into a case study of Google, showcasing strategic maneuvers in IT standardization through alliances and community engagement. This specific example, when considered alongside the broader scenarios presented by Choi et al. (2019) and Teubner et al. (2021), suggests a complex strategy where large corporations utilize both formal and informal networks to sway standard-setting outcomes. The role of proximity in these interactions, particularly how close or distant relationships among consortium members might influence the strategic behavior of large corporations, remains an underexplored area that warrants further investigation. This insight is vital but also highlights the need for broader research that encompasses a variety of large corporations across consortia, offering a more comprehensive view of their strategic positioning and impact in standard-setting networks, with a particular focus on how proximity affects these dynamics.

The research by Lee and Sohn (2018) and Blind, Kenney, Leiponen, and Simcoe (2023) further enriches this narrative. Lee and Sohn (2018) challenge the idea that standardization impedes innovation, proposing instead that it can promote technological diversity. This perspective is complemented by Blind et al. (2023), who focus on the significance of standards in the digital era, particularly the interplay between open-source software (OSS) and formal standardization. These studies collectively suggest a dynamic and collaborative standard-setting environment where large corporations are not only participants but also key influencers in shaping innovation. However, they leave the specific strategies and impacts of large corporations within this environment unexplored, particularly in relation to how different forms of proximity might influence these processes, a gap that aligns with the earlier described research potentials.

Moon and Lee (2021) contribute to this discussion by offering a structured understanding of the primary actors in technology standardization. Their categorization based on roles and timing of engagement provides a framework to analyze how large corporations strategically navigate standard-setting networks. However, their work stops short of a detailed exploration of the strategic influence these actors exert, especially in terms of shaping standards and driving innovation. Additionally, the role of proximity in determining the influence of these actors remains a critical but underexamined area, highlighting the need for research that investigates how proximity—whether geographic, technological, or organizational—affects the strategic actions of large corporations within consortia.

2.3 Knowledge gap

The involvement of large corporations within consortia and their impact on standard-setting presents a critical knowledge gap in current literature, particularly in technology and business contexts. While the studies we have discussed provide valuable insights into the processes of standard-setting and the roles of various stakeholders, they collectively highlight a significant gap in understanding how large corporations position themselves and exert influence within these networks.

This gap becomes more apparent when we consider how factors like geographic and technological proximity shape the influence that large corporations can wield. Proximity not only affects the nature of collaboration but also influences how power is distributed within the standard-setting process. For example, geographic proximity can lead to more frequent interactions, fostering the trust needed for large corporations to assert their influence within consortia. Similarly, technological proximity can facilitate smoother communication, creating environments where the established technological frameworks of larger firms might overshadow the innovative contributions of smaller entities.

Our focus is on understanding how large corporations navigate the balance between promoting innovation and aligning standards with their corporate objectives. These corporations, with their substantial resources, industry influence, and technical expertise, are positioned to make significant contributions to the development of robust and comprehensive standards. Their involvement can accelerate innovation, ensure broader industry acceptance of standards, and result in standards that reflect current technological and market realities. However, this influence can also be a double-edged sword. When large corporations dominate standard-setting consortia, there is a risk that the standardization process may be skewed in favor of their proprietary interests, rather than addressing the broader needs of the industry.

This potential for dominance could hinder innovation from smaller companies and new entrants, limit the diversity of perspectives in standard development, and lead to the creation of standards that favor established technologies over emerging, potentially disruptive innovations. Additionally, when standards are predominantly shaped by large corporations, they may become less flexible and adaptable to changing market conditions, which could impact their long-term success and relevance.

Addressing this gap is essential for developing a comprehensive understanding of the landscape of technology and business standards. By examining how factors such as proximity and corporate influence interact within consortia, we can gain deeper insights into how these elements together shape the standard-setting process. Our approach will provide valuable perspectives on the collective influence of these factors on technological innovation, industry evolution, and policy formulation, ultimately offering a more nuanced understanding of the role large corporations play in shaping the future of standards.

2.4 Theoretical Framework

Building on the identified gap regarding the strategic influence of large corporations within standards networks, this chapter introduces a theoretical framework aimed at unraveling the complexities of corporate dominance in standards consortia. It acknowledges the significant role that large corporations play in shaping the outcomes of these consortia and seeks to explore how these entities use their positions not only to foster innovation but also to drive standards in ways that align with their corporate goals.

Independent and Dependent Variables

The dependent variable in this study is the success of consortia. Success is defined as the ability of a consortium to achieve its intended outcomes, including the development and implementation of effective industry standards, the facilitation of innovation, and the creation of a sustainable, collaborative environment that benefits all members. This success can be measured by the extent to which consortia achieve these goals and the broader impact of their standards within the industry, which will be elaborated on later. The independent variables considered in this study include:

Large Company Dominance: This variable represents the degree of influence that large corporations exert within a consortium. It includes aspects such as decision-making authority, control over resources, and the capacity to shape the consortium's agenda. The involvement of large corporations can offer significant advantages, such as greater financial stability, access to high-value technologies, and stronger market influence (Schilling & Phelps, 2007). However, an over-representation of large companies may lead to power struggles, as each entity might attempt to steer the consortium's activities toward its own strategic interests, potentially at the expense of the collective goal. Such dominance may result in power imbalances, overshadowing the contributions and needs of smaller companies and stakeholders, which could distort the collaborative balance (Bouncken, Gast, Kraus, & Bogers, 2015).

Geographic Proximity: Defined as the physical closeness between consortium members, this variable influences how easily and frequently members can interact, share knowledge, and collaborate. Geographic proximity facilitates interaction and collaboration by promoting face-to-face communication, trust-building, and easier knowledge exchange (Gertler, 2003; Storper & Venables, 2004). However, there are potential drawbacks, such as the risk of an echo chamber effect, where proximity leads to homogeneity of ideas and perspectives, potentially stifling innovation (Letaifa & Rabeau, 2013). Additionally, spatial lock-in can occur, where firms become overly dependent on their immediate networks, limiting their ability to explore broader, potentially more beneficial networks outside their local environment (Molina-Morales, Garcia-Villaverde, & Requena, 2011). The impact of geographic proximity on consortium success depends thus on its interaction with other factors, with certain configurations enhancing collaboration and others potentially restricting the diversity needed for innovation."

Technological Proximity (Cognitive Proximity): This variable refers to the similarity in knowledge bases, technological expertise, and cognitive frameworks among consortium members. It influences the effectiveness of communication and the ability to collaborate on technical aspects of innovation. High levels of technological proximity can streamline communication, reduce misunderstandings, and foster an environment conducive to innovation (Hansen & Mattes, 2018). However, if all members have very similar technological backgrounds, it may limit the diversity of ideas, which is critical for driving innovation. Conversely, too much technological diversity can hinder effective communication and mutual understanding, potentially challenging collaboration (Marek, Titze, Fuhrmeister, & Blum, 2016). Specific configurations of technological proximity, whether involving higher or lower levels, can thus either facilitate or hinder innovation depending on the broader context within the consortium.

Influence of Independent Variables on the Dependent Variable

The success of a consortium is influenced by a complex interplay of multiple independent variables, each contributing to the overall effectiveness of collaboration, decision-making, and innovation. These variables do not act in isolation but are part of a broader, interconnected framework where their interactions produce specific configurations that determine the outcomes of consortia. Understanding these configurations is essential for identifying the conditions under which consortia are most likely to succeed.

Large Company Dominance Large Company Dominance is a critical factor in determining the success of a consortium. Large corporations often bring significant resources, industry influence, and technical expertise, all of which can enhance the consortium's ability to meet its goals. Their involvement is typically seen as a stabilizing force, providing financial backing, access to advanced technologies, and a strong market presence (Schilling & Phelps, 2007). These contributions can lead to a consortium that is better equipped to tackle complex challenges, develop industry standards, and drive innovation.

However, the influence of large companies is not always straightforward. The impact of large company dominance on consortium success is contingent upon how this dominance interacts with other factors. For instance, while large companies can provide crucial resources, their dominance may also lead to power imbalances within the consortium. When a few large companies exert disproportionate influence, they may steer the consortium's activities toward their own strategic interests, potentially at the expense of smaller members. This can lead to conflicts of interest, reduce the diversity of ideas, and stifle the collaborative spirit that is essential for innovation (Bouncken et al., 2015).

Moreover, if large company dominance is not balanced with other factors, such as geographic and technological proximity, it can result in a consortium that is less adaptive and less inclusive of the contributions from smaller firms. On the other hand, a consortium with too few large companies might struggle with limited resources, lack of market influence, and challenges in scaling its initiatives. Thus, the success of a consortium does not solely depend on the presence of large companies but on how their dominance interacts with and is moderated by other factors within the consortium's configuration. Therefore, we hypothesize:

Hypothesis 1: The dominance of large companies within a consortium is a key factor influencing its success, with particular degrees of large company presence associated withhigher success rates.

Geographic Proximity

Geographic Proximity plays a fundamental role in the success of consortia by influencing the frequency and quality of interactions among members. Geographic proximity refers to the physical closeness between consortium members, such as firms, institutions, or individuals, that facilitates more frequent face-to-face interactions, fosters trust, and enhances the efficiency of knowledge exchange (Gertler, 2003; Storper & Venables, 2004). When consortium members are geographically close, they can more easily engage in informal discussions, build stronger relational ties, and respond quickly to emerging challenges or opportunities.

However, the benefits of geographic proximity are not without their complexities. While physical closeness can enhance collaboration, it can also create the risk of an echo chamber effect, where the homogeneity of ideas and perspectives stifles innovation. When consortium members are too similar in their geographical and cultural backgrounds, they may be less likely to challenge each other's assumptions or introduce novel ideas, leading to a less dynamic and innovative environment (Letaifa & Rabeau, 2013). Additionally, the issue of spatial lock-in arises when firms become overly dependent on their immediate local networks and resources. This reliance can limit their ability to explore and integrate broader, potentially more beneficial networks and resources outside their local environment, thereby constraining the consortium's overall innovation potential (Molina-Morales et al., 2011).

The impact of geographic proximity on consortium success is therefore influenced by how it interacts with other variables, such as large company dominance and technological proximity. For example, geographic proximity may enhance the effectiveness of large company dominance by facilitating better communication and coordination. Conversely, if geographic proximity is not balanced with sufficient diversity in other areas, it may lead to a less innovative and less resilient consortium. Therefore, we propose:

Hypothesis 2: Geographical proximity among consortium members is a key factor influencing the success of the consortium, where particular degrees of proximity are associated with higher success rates.

Technological Proximity

Technological Proximity (also referred to as cognitive proximity) is another crucial factor that affects the success of consortia by determining how well members can collaborate on technical matters. Technological proximity refers to the extent to which consortium members share similar knowledge bases, technological expertise, and cognitive frameworks, which facilitates mutual understanding and learning (Hansen & Mattes, 2018). High levels of technological proximity can streamline communication, reduce misunderstandings, and create an environment that is conducive to collaborative problem-solving and innovation.

However, the relationship between technological proximity and innovation is complex. While shared cognitive frameworks can enhance collaboration, excessive technological similarity can lead to a lack of new perspectives and ideas, which are critical for driving innovation. Without sufficient diversity in technological backgrounds, a consortium may become too focused on incremental improvements rather than breakthrough innovations. On the other hand, too much diversity in technological backgrounds can hinder effective communication and collaboration, as members may struggle to understand and integrate each other's contributions (Marek et al., 2016).

Therefore, the success of a consortium depends on achieving the right balance of technological proximity and diversity. This balance is further influenced by how technological proximity interacts with other factors, such as large company dominance and geographic proximity. For instance, a consortium with high technological proximity might succeed if it is complemented by a diversity of perspectives in other areas or if large companies provide the necessary resources to bridge gaps in understanding. Thus, we hypothesize:

Hypothesis 3: The success of a consortium is influenced by the level of technological proximity among its members, where particular degrees of technological diversity are associated with higher success rates.

Interaction of Independent Variables

The success of a consortium is not determined by any single factor but rather by the complex interplay of multiple independent variables, specifically large company dominance, geographic proximity, and technological proximity. These variables interact in specific configurations that either facilitate or hinder collaboration, innovation, and overall effectiveness within the consortium.

For instance, a consortium may thrive when large company dominance is balanced with the right levels of geographic and technological proximity, fostering both stability and innovation. Alternatively, a consortium with less dominant large companies might succeed through a configuration of high technological diversity and geographic proximity, encouraging more dynamic and inclusive collaboration.

Understanding these interactions requires an integrative approach that goes beyond examining the individual impact of each variable. Instead, we focus on how various combinations of these factors influence consortium outcomes. By considering the specific configurations in which these variables interact, we aim to identify the conditions that lead to successful consortium outcomes. Building on the established hypotheses, and following the framework of Raab, Mannak, and Cambré (2013), hypothesis 4 aims to investigate the combined influence of large company dominance, geographic proximity, and technological proximity on the success of consortia. By considering various combinations of these variables, this hypothesis seeks to identify specific configurations that lead to successful consortium outcomes. The hypothesis is formulated as follows:

Hypothesis 4: The success of a consortium is determined by specific configurations of large company dominance, geographic proximity, and technological proximity. High success rates are associated with particular combinations of these variables, rather than the presence of any single factor alone.

In sum, this theoretical framework integrates key dimensions of consortium composition and proximity to provide a comprehensive understanding of how these factors interact to influence consortium success. By focusing on the configurations of large company dominance, geographic proximity, and technological proximity, we aim to identify the specific conditions under which consortia are most likely to succeed. This approach allows us to examine the collective influence of these variables on the success of standard-setting activities, offering a nuanced perspective on the factors that contribute to or hinder the effectiveness of consortia.

3 Research methodology

3.1 Research design

The study of consortia presents unique challenges due to the complex interplay of various factors such as large company dominance, geographical proximity, and technological proximity (Simcoe, 2012). These factors, while crucial for the success of consortia, create intricate dynamics that are difficult to analyze using traditional research methods. Given the relatively small number of cases typically involved in consortia research, there is a need for a methodological approach that can handle this complexity while preserving the depth of qualitative insights. To address these challenges, this study adopts the Qualitative Comparative Analysis (QCA) approach, which is particularly well-suited for exploring the multifaceted and interdependent nature of the variables at play in consortia (Fiss, 2011). QCA is a method that bridges qualitative and quantitative research, allowing for the systematic comparison of multiple cases while preserving the richness of qualitative data. Originally developed by Charles C. Ragin in the late 1980s, QCA is particularly well-suited for research involving complex causality and where the number of cases is moderate, typically between 10 and 50 (Ragin, 1987).

QCA employs Boolean algebra to identify patterns of conditions that lead to a particular outcome, enabling researchers to pinpoint necessary and sufficient conditions. This method is advantageous for exploring phenomena where traditional statistical methods may not be applicable due to small sample sizes or the need for in-depth case analysis (Rihoux & Ragin, 2009). The configurational approach of QCA allows for the consideration of multiple conjunctural causation, meaning that it recognizes that different combinations of conditions can produce the same outcome.

In QCA, crisp and fuzzy sets are two methodological approaches used to classify and analyze data, which both have been employed in this study to address the varying nature of the variables involved. Crisp sets, also known as binary or dichotomous sets, involve variables that can take on one of two values: either 0 or 1. In this framework, a case either fully belongs to a set (membership value of 1) or does not belong to the set at all (membership value of 0). This binary classification makes crisp sets straightforward but potentially limited in capturing the complexity of social phenomena (Rihoux & Marx, 2013). Fuzzy sets allow for degrees of membership, meaning that cases can belong to a set to varying extents, ranging from 0 to 1. This enables a more nuanced analysis that can reflect partial membership in a set. Despite this flexibility, it is still important to classify data into categories as distinctly as possible, ideally avoiding values close to 0,5 to reduce ambiguity and increase the precision of the analysis. Furthermore, as few categories as possible should be used, since using fewer categories in fuzzy sets simplifies the model, enhances interpretability, improves robustness, eases calibration, and reduces ambiguity, making the analysis more effective and reliable. (Rohlfing, 2020).

The suitability of QCA for this study stems from several factors. Firstly, the complexity and multifaceted nature of corporate influence within consortia aligns well with QCA's strength in handling complex causation. Specifically, this study examines three independent variables: large company dominance, geographical proximity, and technological proximity. QCA's ability to handle multiple interdependent variables and explore their combined effects on consortia success makes it an ideal choice. Secondly, the sample size of 40 consortia is ideal for QCA, as it falls within the range where QCA can effectively analyze and compare cases without oversimplifying the data. Lastly, QCA's ability to integrate qualitative insights with systematic comparative analysis provides a robust framework for understanding the nuanced dynamics within consortia.

Numerous studies have successfully employed QCA in various fields, demonstrating its versatility and effectiveness. For instance, Fiss (2011) utilized QCA to explore the configurations of organizational design elements and their impact on firm performance. Similarly,Crilly, Zollo, and Hansen (2012) applied QCA to examine how corporate social responsibility influences firm performance across different contexts. Additionally, a study by Greckhamer, Misangyi, Elms, and Lacey (2007) used QCA to analyze the impact of cultural and institutional factors on entrepreneurial activities, highlighting the method's ability to uncover complex interaction effects.

In the context of this research, QCA enables the identification of specific configurations of consortium characteristics and corporate influence that contribute to successful standardization outcomes. By systematically comparing cases, QCA can reveal the diverse pathways through which large corporations, geographical proximity, and technological proximity impact consortia.

To implement the QCA approach, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) was employed, utilizing the fs/QCA software developed by Charles Ragin (Ragin, 2024). This software is specifically designed for QCA and incorporates fuzzy set theory, allowing for a more detailed analysis of complex causal relationships. The fs/QCA software was used to perform key steps in the analysis, including the calibration of raw data into fuzzy or crisp sets, the construction of truth tables, and the identification of causal configurations leading to successful consortium outcomes. The software's ability to handle both crisp and fuzzy sets made it particularly suitable for this study, providing the flexibility needed to analyze the nuanced variations in the data and capture the complex interactions between the variables.

3.2 Case Selection and Sampling Strategy

Case Selection and Data Collection This study focuses on consortia within the Audio, Video, and Multimedia sector, using a dataset sourced from consortiuminfo.org, which initially included 138 identified consortia. Consortiuminfo.org is a well-established online resource dedicated to providing detailed information about industry consortia across various sectors. It aggregates data that is often difficult to obtain elsewhere, including insights into the structure, membership, and activities of consortia. This makes it a particularly valuable tool for researchers and industry professionals interested in the dynamics of standard-setting processes.

The selection of the Audio, Video, and Multimedia sector was motivated by its prominent role in driving technological innovation and its substantial influence on the development of industry standards. This sector plays a crucial part in advancing consumer electronics, where standards ensure the compatibility and interoperability of products like televisions, media players, and streaming devices. These products are widely recognized and used, making the standards created in this sector relatively easy to understand and assess in terms of their success. The visibility and importance of these standards in everyday consumer technology provided a strong rationale for focusing on this sector, as it offers clear examples of how standard-setting consortia can impact both industry and consumers.

Given the broad scope of the initial dataset, a strategic sampling method was employed to select a manageable subset of 40 consortia for detailed analysis. The selection criteria were designed to ensure that the sample was both relevant and representative of the sector's diversity. Specifically, consortia were chosen based on their relevance to the Audio, Video, and Multimedia sector, the availability of comprehensive data, and their representation in terms of geographical distribution and technological focus. This approach aimed to capture the full spectrum of dynamics within the sector, including variations in how consortia operate across different regions and technologies.

The diversity among the consortia is crucial for exploring the different pathways through which these variables impact consortia success. By including a mix of large, influential consortia and smaller, specialized ones, the analysis captures a wide range of dynamics within the sector. This representative sample ensures that the findings are broadly applicable and provide insights into the factors that contribute to the success of consortia in setting industry standards.

Priority was given to consortia that provided extensive and accessible data on their goals, membership, and activities. This information was primarily extracted from the consortia's websites listed on consortiuminfo.org and was supplemented by additional data sourced from the websites of member companies. By including a mix of large, influential consortia and smaller ones, the study aimed to reflect the full range of interactions and dynamics within the sector. This diverse subset of 40 consortia was selected to enable a comprehensive analysis of the influence of large company dominance, geographical proximity, and technological proximity on the success of standard-setting consortia.

Data Collection Methods

The data collection process was carefully organized to ensure the accurate and detailed capture of information about each consortium and its member companies, which formed the basis for the analysis in this study. This process was managed using an Excel workbook, which served as a centralized repository for all the collected data and was essential for the subsequent data analysis.

Initially, each selected consortium was recorded in an Excel sheet titled "consortia info." This sheet included detailed information for each consortium, such as the consortium's name, its primary goals, and other relevant structural details. A crucial part of this process involved compiling an overview of the member companies associated with each consortium. This information was gathered by visiting the respective consortium websites, where the names of all member companies were manually recorded. Additionally, their roles within the consortium, such as board member, steering member, associate member, or supporting member, were documented in separate columns. This step provided a comprehensive view of the consortium's structure and the roles that different companies played within it.

Following the documentation of consortium membership, the next phase of data collection focused on gathering detailed information about each of the 1620 companies that were part of the consortia. This data was meticulously recorded in another Excel sheet titled "company info." Given the large number of companies involved, manually checking each company's website for information was impractical. To streamline the process and ensure data accuracy, LinkedIn was used as the primary source for collecting company-specific information. LinkedIn is widely regarded as a reliable platform for gathering current and accurate data, as companies frequently update their profiles to reflect their latest developments and professional standing. The credibility of LinkedIn data for academic research is well-supported, as demonstrated by studies such as those by Jain and Dubey (2020), who used LinkedIn data to build a graph database, and Tsironis, Karagkouni, Dimitriou, and Tsagarakis (2023), who utilized LinkedIn to map sustainable practices within the transportation sector.

For each company, data on the location of headquarters, number of employees, LinkedIn sub-industries, and founding year were collected and systematically recorded. This information was linked to other relevant details in the Excel sheet, including a unique identifier for each company, its association with a consortium, the company's role within the consortium, and a link to its LinkedIn profile for reference. This comprehensive dataset, consisting of nine columns and 1621 rows including a header row, provided a detailed and organized overview of the companies and their roles within the consortia.

To ensure the reliability of the data collected from LinkedIn, each company's LinkedIn page was cross-referenced with information from the consortium websites. This involved verifying that the company name and logo matched those listed on the consortium's website and ensuring that the LinkedIn profile was a professional page with an appropriate number of followers relative to the company's size. In cases where LinkedIn profiles were not available, especially for companies in Asia such as those in China, Japan, and South Korea, alternative sources such as the company's official website were consulted to obtain the necessary information. Japanese companies, for example, often have detailed company profile pages on their websites, which provided the required data.

This thorough approach resulted in only 12 missing values across the dataset. These missing values were adjusted to zero in the dataset to ensure consistency. Given the minimal impact of these missing values on the overall analysis, the adjustment was deemed justifiable. The thoroughness of the data collection process ensures that the dataset is both accurate and comprehensive, providing a solid foundation for analyzing the factors influencing the success of standard-setting consortia.

3.2.1 Consortium success

After all the company information was gathered and completed, the analysis was refocused on the consortium level. An important factor that needed to be determined was consortium success. Measuring and defining the success of consortia is a complex and multifaceted task, largely due to the diverse goals, stakeholders, and operational contexts they operate within. This diversity results in varied criteria for success, making it challenging to develop a universal metric. According to Das and Teng (2000), the performance of collaborative ventures such as consortia is inherently difficult to evaluate due to their multifaceted nature. Also, the paper highlight that consortium performance evaluation requires a nuanced approach that considers specific objectives and contexts. Therefore, a comprehensive approach is necessary to capture this complexity effectively.

To address this complex task, this study employs a self-created multifactor framework to evaluate consortium success, focusing on three key factors: creation of standards, adoption of standards, and scholarly recognition. This point-based framework is designed to provide a balanced assessment of consortium performance, ensuring that both tangible outputs and broader impacts are considered. The proposed framework offers several advantages in evaluating consortium success. Comprehensive coverage is achieved by including multiple factors—creation of standards, adoption of standards, and scholarly recognition. This captures a broad spectrum of consortium activities and impact, ensuring that both immediate outputs and longer-term influences are considered. The framework balances qualitative and quantitative measures, combining direct evidence of standard creation and adoption with scholarly recognition. This approach mitigates the limitations of using a single metric and provides a more nuanced understanding of consortium success. Additionally, the scoring system within each criterion allows for varying levels of success to be recognized. This flexibility ensures that consortia with different focuses and operational scales can be fairly assessed. By relying on verifiable and documented evidence for scoring, the framework enhances the reliability of the evaluation. The use of official documentation and academic citations as sources ensures that the assessment is based on credible and objective data.

The following sections will detail the specific criteria used to measure the creation of standards, the adoption of those standards, and their scholarly recognition. Each variable is crucial for capturing different aspects of consortium performance and provides a structured framework for assessment. The detailed point-based scoring system for each criterion will be explained in subsequent sections, illustrating how the framework quantifies consortium success.

Success Criterion 1 : Created standard(s)

The creation of standards is a fundamental measure of a consortium's output and effectiveness. It demonstrates the consortium's ability to collaborate and develop formalized guidelines or protocols that can influence industry practices. The success indicator "created standards" determined based on the following inclusion and exclusion criteria:

- **Inclusion Criteria**: Documentation or announcements on the consortium's official website, annual reports, or other official publications confirming the creation of one or more standards.
- **Exclusion Criteria:** Lack of documented evidence of standard creation,

Based on these criteria the success indicator got classified as follow:

- **0 (No):** No standard has been published.
- **(Yes):** A standard has been formally developed and approved by the consortium.

Success Criterion 2 : Standard adoption

The adoption of standards reflects the practical impact and acceptance of the consortium's work in the market. It shows whether the developed standards are being implemented and utilized by the industry, indicating their relevance and utility.

To establish a reliable and justifiable determination of adoption, a comprehensive approach was taken that included reviewing information about the consortium, the standards developed, the associated products, and their impact on the market. This involved analyzing multiple news sources and websites, which provided insights into usage data, market reports, and other qualitative indicators to assess the degree to which the standards have been adopted. By considering a range of evidence, including market penetration, industry uptake, and real-world applications, a nuanced understanding was developed. This method allowed for the creation of a well-informed perspective on how significant the standards are and what impact they have on the market.

For transparency and verification, evidence supporting the classification of adoption rates for each consortium was documented in the Excel file (..source...) under the "adoption" row. This documentation includes specific references and reasons for assigning particular adoption scores, enhancing the reliability and justification of the evaluation.

The success indicator "adoption of standards" is determined based on the following inclusion and exclusion criteria:

- Inclusion Criteria: Evidence of market implementation and impact, such as usage data, market reports, or adoption in specific industry sectors.
- Exclusion Criteria: Lack of evidence or minimal impact on the market.

Based on these criteria, the success indicator is classified as follows:

- 0 points (No or minimal impact): The standard has not been implemented in the market or has minimal impact.
- 2 points (Moderate impact): The standard is implemented in a niche market or limited geographical areas (e.g., less than 10
- 3 points (Significant impact): The standard is globally accepted and widely used (e.g., more than 50

Success Criterion 3 : Scholarly Recognition

Scholarly recognition indicates the academic and research community's acknowledgment of the consortium's work. High citation counts and references in academic literature suggest that the standards are considered valuable and influential in advancing knowledge and practice.

The success indicator "scholarly recognition" is determined based on the following inclusion and exclusion criteria:

- Inclusion Criteria: Citations of the consortium's work in academic databases. Specific search terms include: ("Consortium name" AND "consortium" AND "success") OR ("Consortium name" AND "consortium" AND "impact") OR ("Consortium name" AND "consortium" AND "recognition").
- Exclusion Criteria: Fewer than 10 citations or minimal academic engagement.

Based on these criteria, the success indicator is classified as follows:

- 0 points (No or minimal): Fewer than 10 scientific articles or studies about the standard.
- 2 points (Moderate): There are a moderate number of scientific publications about the standard (10-99 articles in reputable journals or conferences).
- 3 points (Extensive): There is extensive scientific literature available (100 or more hits on Google Scholar or several review articles discussing the standard).

Scoring system

Based on the scoring system, consortium success is categorized into two levels of success: moderate- and/or high success.

Moderate success is defined by achieving a total score of the three criteria of 4 or higher. This includes standards with moderate success and moderate recognition that have created a standard, as well as standards with extensive literature recognition but moderate market adoption. This categorization is justified as it indicates that the standard is innovative and well-regarded, though the market or related technologies may not yet be ready for widespread adoption.

High success is defined by achieving a total score of 7, indicating that highly impactful standards have been created, with significant market adoption and extensive scholarly recognition. This level of success suggests that the standards are not only innovative but also have substantial market impact and academic acknowledgment, demonstrating leadership and influence in the industry.

3.3 Calibration of Data

Now that all data for all variables have been collected, they need to be calibrated to make them usable for QCA analysis. In this paragraph, we will discuss how this has been done for each variable.

The data used in the QCA were calibrated into binary and fuzzy sets to facilitate the analysis. This calibration process involved converting the raw data into a format suitable for QCA, allowing for the systematic comparison of cases. The binary dataset includes all the variables coded as either 0 (absence) or 1 (presence). The fuzzy dataset allows for varying degrees of membership, providing a more nuanced analysis. Variables are calibrated into categories (e.g., 0, 0.25, 0.5, 0.75, and 1) to reflect partial membership in each set. In appendix 7 both the overview for the calibrated binary dataset as for the calibrated fuzzy dataset is presented.

3.3.1 Consortium success - dependent variable

The dependent variable, success, as previously discussed, is measured and classified at two levels: moderate success and high success. This variable is straightforward to calibrate into binary values due to the measurement method employed. In the Excel file, the scores for each consortium were summed, and an if-else statement was created to convert these scores into binary values.

For moderate success, a total score of 4 or higher across the three success criteria was required. This approach allows for multiple forms of success to be captured. For instance, one way a consortium could achieve moderate success is by creating a standard (score 1), having moderate market impact (score 2), and gaining moderate scholarly recognition (score 2). This scenario would yield a total score of 5, thereby classifying the consortium as having moderate success because it has created a standard and has reasonable impact in both the market and academia. Another scenario for moderate success could involve a consortium that has created a standard (score 1) but has no market impact (score 0), yet has significant scholarly recognition (score 3). This indicates that a high-quality, innovative standard has been developed, but it has not yet been adopted in the market. This situation is still considered a success because the consortium's work has substantial academic value, suggesting potential for future market impact once the market is ready.

To also identify the most impactful and innovative consortia, a high success indicator was added. High success is only assigned if the consortium achieves the highest possible score of 7. This stringent criterion ensures that only the most successful consortia are highlighted.

The result was a comprehensive overview of 40 consortia, each evaluated for moderate or high success through the assignment of a binary score. In this system, a score of 0 indicates no success, while a score of 1 indicates success.

3.3.2 Large company dominance - independent variable

The concept of large company dominance in consortia is somewhat ambiguous and open to interpretation. The literature does not provide a universally accepted definition or method for quantifying this phenomenon, which presents a challenge when attempting to measure it in a systematic way. However, previous research in related fields has attempted to quantify corporate influence through various means, such as the analysis of board positions, ownership stakes, or resource contributions (Mizruchi, 1996; Pfeffer & Salancik, 1978).

In response to the need for a more comprehensive measure of dominance within consortia, this study has developed the "Combined Dominance Score" (CDS). This formula is designed to represent and integrate different forms of dominance, both direct and indirect, that a company may exert within a consortium. The formula is expressed as follows:

Combined Dominance Score (CDS) = 0.5 *BPP + 0.5 * HP

The Board Position Proportion (BPP) reflects the direct influence a company exerts through its governance roles, particularly board positions. This measure aligns with research that has highlighted the importance of board representation in corporate governance as a means of exerting influence (Zahra & Pearce, 1989). Meanwhile, the Holding Proportion (HP) accounts for the indirect influence of a company, such as its financial contributions or ownership stakes, a concept often discussed in studies of corporate power and resource control (Pfeffer & Salancik, 1978).

While the Combined Dominance Score is a novel formula developed for this study, the approach of quantifying influence through a combination of direct and indirect measures has precedents in other research domains. For example, studies on corporate governance and strategic alliances have often employed similar methodologies to assess influence by combining variables like board presence and equity stakes (Gulati & Westphal, 1999; Hillman, Cannella, & Paetzold, 2000). However, there appears to be no direct application of such a formula specifically within the context of standard-setting consortia.

The CDS therefore represents an adaptation of existing ideas from broader organizational research to the specific context of consortia. It is informed by established methods of measuring influence but tailored to the unique dynamics of standard-setting bodies, where both governance roles and resource contributions play crucial roles in determining dominance. This formula provides a structured way to quantify the influence of large companies, enabling a more precise analysis of power dynamics within consortia.

$$\text{Board Position Proportion (BPP)} = \frac{\text{Number of Board Positions Held by the Company}}{\text{Total Number of Board Positions in the Consortium}}$$

Figure 1: BPP formula

The Headcount Proportion (HP) refers to the ratio of a company's headcount to the total headcount of all companies within the consortium. This measure represents the indirect power large companies possess through their resources relative to smaller companies in the consortium. Larger companies, by virtue of their more extensive resources, can leverage their workforce, financial strength, and operational capabilities to exert influence. This can include swaying decisions, shaping consortium policies, and potentially overshadowing smaller companies' interests. Even without a board position, larger companies can exert considerable influence on smaller consortium members, which may or may not be in the board, through these means.

The total formula for the combined dominance score is thus:

The combination of these two factors, direct influence through board positions and indirect influence through resource allocation, provides a comprehensive measure of power dynamics within a consortium.

$$\text{Headcount Proportion (HP)} = \frac{\text{Company's Headcount}}{\text{Total Headcount of All Companies in the Consortium}}$$

Figure 2: HP formula

$$\text{CDS} = 0.5 \times \left(\frac{\text{Number of Board Positions Held by the Company}}{\text{Total Number of Board Positions in the Consortium}}\right) + 0.5 \times \left(\frac{\text{Company's Headcount}}{\text{Total Headcount of All Companies in the Consortium}}\right)$$

Figure 3: CDS formula

Both factors are weighted equally in the CDS formula to reflect their balanced contribution to overall dominance. The rationale for this equal weighting lies in the understanding that both direct decision-making power and the capability to influence through resources are critical to assessing a company's overall dominance within a consortium. By integrating these elements, the CDS provides a quantifiable measure of power distribution, enabling a more nuanced understanding of how influence is exercised and maintained among consortium members, including the significant yet often underestimated role of smaller companies.

Defining large company

Now that the formula to determine large company dominance has been established, it is essential to define what is meant by "large companies." This is not a straightforward task, as there is no universally accepted definition. The options and interpretations are numerous, and this study considers two primary approaches to defining large companies.

European guidlines

Firstly, we follow the European guidelines for determining company sizes. To categorize the size of an organization, various standards have been created worldwide. For this study, we adhere to the "User Guide to the SME Definition" by the European Commission (European Commission, Directorate-General for Internal Market, & SMEs, 2020). Given that the data encompasses consortia from around the globe, the term "large company" can vary significantly depending on regional definitions. Therefore, a consistent categorization is necessary to facilitate accurate comparisons.

Since this research is conducted in the Netherlands, it is practical to follow the European guidelines. Additionally, these guidelines are comprehensive, incorporating several factors into the categorization, unlike some other international standards. This thorough approach ensures a well-considered classification of company sizes.

According to the User Guide to the SME Definition, an organization's size is determined by the number of employees and either annual revenue or the annual balance sheet total. The guidelines categorize organizations into micro, small, and medium-sized enterprises (SMEs). Any organization that does not fit into these categories is considered a large company. The table below illustrates these classifications:

Enterprise category	Headcount: annual work unit (AWU)	AND	Annual turnover in EUR €	OR	Annual balance sheet total in EUR €
Micro	<10	AND	$\leq 2 million$	OR	≤ 2 *million*
Small	<50	AND	$\leq 10 million$	OR	≤ 10 *million*
Medium	<250	AND	$\leq 50 million$	OR	≤ 43 *million*
Large	If not classifiable in any of the above categories				

Table 1: User guide to the SME Definition (European Commission et al., 2020)

While the European guidelines provide a comprehensive framework for categorizing company sizes based on multiple factors, this study relies solely on headcount to determine company size. This decision was made due to the ease and speed of obtaining employee data from LinkedIn, which was readily available for most companies. Given the scope of the research and the large number of companies involved, using headcount as the primary metric was the most practical approach to ensure timely and consistent data collection.

Top 10%

In the first method, companies with more than 250 employees are included in the CDS calculation. This could result in high dominance scores for many companies, potentially diluting the specificity of the analysis. To address this, a second method was developed, assessing dominance based on the top 10% of companies within a consortium. This method evaluates relative dominance by focusing on the most influential companies, rather than a fixed employee threshold, providing a more nuanced understanding of dominance.

The analysis began by determining the total number of companies in the dataset, then calculating 10% of this total. To ensure inclusivity, especially in smaller datasets, this number was rounded up to the nearest whole number. For instance, in a dataset of 30 companies, 10% would be three companies. This method ensured robustness and meaningful analysis, even with fewer companies. Next, companies were ranked in descending order based on employee count. The top 10% of companies, those with the highest number of employees, were then isolated for further analysis for the CDS.

This methodology is straightforward yet robust. It defines the dataset's scope, ensures inclusivity, and identifies the most significant companies by employee count. Focusing on the top 10% provides meaningful insights into the most impactful companies. This structured approach ensures consistent, reliable, and reproducible analysis, enhancing the credibility of the results and providing a clear framework for examining significant companies within the dataset.

Calibration

The calculation of the Consortium Dominance Score (CDS) was conducted using two distinct methodologies. The first method included only companies with more than 250 employees, while the second method considered only the top 10% of companies by size.

In the attached Excel file, within the sheet named "Company size variable," both the number of employees per company and the corresponding CDS calculations are provided. LinkedIn classifies employee numbers within ranges, and for the sake of these calculations, the midpoint of each range was used. An alternative approach using the minimum and maximum values of the ranges was also considered; however, this approach resulted in a distribution where a large number of companies either fell into or out of the European guideline categories, causing instability. The use of the midpoint maintained a more consistent distribution.

After calculating the CDS for each company, which indicates the company's influence within the consortium, the CDS values were summed based on the two methods to derive a CDS for the entire consortium. This resulting score ranges between 0 and 1, where a score closer to 1 indicates greater influence by large companies within the consortium. In the Excel file, columns X and Z show the summed CDS values for each consortium for the methods considering companies with more than 250 employees and the top 10% of companies, respectively.

Preparation for QCA

Since the CDS is continuous data, it had to be converted for the QCA analysis into either a crisp set (binary) or a fuzzy set (categorical). Due to the unknown effects, both conversion options were tested. In both cases, the median was used as the basis for categorization. Initially, a threshold of 0.5 was considered, implying that large companies would dominate if their CDS was 0.5 or greater. However, this threshold proved impractical, as most data points exceeded this value, particularly using the first method (250 employees), limiting the potential for meaningful analysis. Therefore, the median was used to determine relative dominance within consortia.

For the crisp set, the categories were defined based on whether the CDS was above or below the median. The median for the first method (250 employees) was 0.9481, and for the second method (top 10%) was 0.5087. Data points equal to or below the median were classified as 0, while those above were classified as 1. The fuzzy set was categorized into four groups. Since QCA compares categories with the strongest association to 0 or 1, no category could be centered around 0.5 to avoid ambiguity. Thus, four categories were created, determined using the first quartile, median, and third quartile for each method (250 employees and top 10%). These thresholds are described in table 3.

CDS based on 250 employees	
First quartile (Q1):	0,7549
Median (Q2):	0,9481
Third quartile (Q3):	0,9997
CDS based on top 10%	
First quartile (Q1):	0,4158
Median (Q2):	0,5087
Third quartile (Q3):	0,6079

Table 2: Data distribution CDS

Based on these thresholds, four categories were established to classify the data points. Specifically, if a data point is smaller than the first quartile (Q1), it is categorized as 0. A value less than the second quartile (Q2) but greater than or equal to Q1 is assigned a category of 0.25. Similarly, a value less than the third quartile (Q3) but greater than or equal to Q2 is categorized as 0.75. All remaining data points, those greater than or equal to Q3, are classified as 1. This classification scheme avoids placing data points in the middle of the range, thereby enhancing the granularity of the representation compared to binary data, while preventing ambiguity at the midpoint.

3.3.3 Geographical proximity - independent variable

Geographical proximity can be measured in various ways. Boschma (2005); Scherngell and Barber (2009)describe that it is often quantified by calculating the physical distances between consortium members' headquarters or key operational locations, facilitated by Geographic Information Systems. This involves identifying headquarters locations, extracting geographic coordinates from official addresses, and calculating the great circle distance between them. The pairwise distances are then averaged or medians taken to measure overall geographic proximity within the consortium(Balland, Boschma, & Frenken, 2015). Another approach uses regional codes, such as the Federal Information Processing Standards (FIPS) in the United States and the Nomenclature of Territorial Units for Statistics (NUTS) in Europe. These codes classify consortium members into regions and measure proximity based on these classifications. Members in the same region are considered geographically proximate, whereas those in different regions are considered distant. For this research, we foresee that both methods have drawbacks. Physical distance calculations may not accurately reflect consortium proximity, as a single distant company can skew the average, and they do not account for economic and social interactions crucial for collaboration (Boschma, 2005). Regional codes like FIPS and NUTS are difficult to compare across countries and continents, complicating accurate proximity measurement for global consortia.

Since the locations of the headquarters have already been collected and are available at the city level, this information is relatively detailed for comparing consortia worldwide. One way to measure proximity with the current data is by using a Blau index, which quantifies diversity within a group, where a higher Blau's index indicates greater diversity and a lower index indicates higher homogeneity (Solanas, Selvam, Navarro, & Leiva, 2012). The Blau's index formula is as follow:

Blau's index (Variety)	$B = 1 - \sum_{i=1}^{k} p_i^2$

Figure 4: Blau's index formula

Given that there is likely to be limited overlap at the city level, it was decided to also calculate proximity at the country level and the UN geo-subregion level. Calculating proximity at these three levels—city, country, and UN geo-subregion—provides a more comprehensive analysis. The city level offers fine-grained detail, the country level provides a broader perspective, and the UN geo-subregion level, which is a classification system that groups countries into subregions based on geographic and socio-economic similarities, adds an intermediate layer of granularity (United Nations Statistics Division, 2024).

For each depth level of geographical proximity, a Blau's index was created for each consortium. This data can be found in the Excel sheet in "location variable". To determine what constitutes a high or low Blau's index value in terms of geographical proximity, we used the median. Specifically, we calculated the median of all three sets of Blau's index values to achieve an even distribution.

If the median were calculated separately for each depth level, it would mean that approximately half of the data points at each level (city, country, UN geo-subregion) would fall above and below their respective medians. This approach would minimize the differentiation between the three levels, rendering the comparison ineffective. By using the combined median of the Blau's indices, we ensure a more integrated and meaningful comparison across all depth levels. This combined approach enhances the analysis by highlighting the overall distribution and variation in geographical proximity across the different levels, providing a clearer picture of the spatial relationships within the consortia.

Blau's index geographical proximity	
First quartile (Q1):	0,6228
Median (Q2):	0,7535
Third quartile (Q3):	0,9023

Table 3: Data distribution Blau's index geographical proximity

The crisp set was determined by the median of 0.7535. Since a low Blau's index indicates high proximity, the binary variable would be set to 1 if the data point is below the median. If the data point is above the median it indicates low proximity, so it is set to 0.

Based on these thresholds, four categories were established to classify the data points for the fuzzy dataset. If the a data point is smaller than the first quartile (Q1), it is categorized as 1. A value less than the second quartile (Q2) but greater than or equal to Q1 is assigned a category of 0.75. Similarly, a value less than the third quartile (Q3) but greater than or equal to Q2 is categorized as 0.25. All remaining data points, those greater than or equal to Q3, are classified as 0. This classification scheme again avoids placing data points in the middle of the range, thereby enhancing the granularity of the representation compared to binary data, while preventing ambiguity at the midpoint.

3.3.4 Technological proximity - independent variable

To measure technological proximity within this study, the structured classification system named the Global Industry Classification Standard (GICS) will be used. This system provides a systematic way to categorize companies based on their primary business activities and technological expertise.

Developed by MSCI and Standard & Poor's, the GICS is widely used in the financial sector, particularly by investors, asset managers, and researchers who rely on standardized sectors to analyze potential investment assets. This classification method organizes companies into 11 sectors, 25 industry groups, 74 industries, and 163 sub-industries (MSCI Inc., 2023). Its widespread use, especially in the United States, makes it a reliable choice for financial analysis and investment decision-making (Hawkins, 2023). The GICS is an excellent choice for this study because it provides a detailed and universally recognized framework for classifying technological and industrial activities, ensuring consistency and comparability across different firms.

By applying such a classification-based approach, technological proximity can be quantified by determining the concentration of firms within specific sectors, industry groups, or sub-industries. A higher concentration within specific categories indicates greater technological proximity, which can then be correlated with consortium success to examine the hypothesized relationships.

Given that the LinkedIn data provides the primary sector in which companies operate, often at the sub-industry and industry group levels, it was decided to categorize technological proximity at three levels: sub-industry, industry group, and sector. This multi-tiered categorization allows for a more nuanced analysis, offering fine-grained detail at the sub-industry level, broader industry group perspectives, and the overall sector view, thus capturing different layers of technological proximity within consortia.

For each depth level of technological proximity, a Blau's index was created for each consortium. This data can be found in the Excel sheet named "sector variable". To determine what constitutes a high or low Blau's index value in terms of technological proximity, we used the median of all three sets of Blau's index values to achieve an even distribution.

If the median were calculated separately for each depth level, it would mean that approximately half of the data points at each level (sub-industry, industry group, sector) would fall above and below their respective medians. This approach would minimize the differentiation between the three levels, rendering the comparison ineffective. By using the combined median of the Blau's indices, we ensure a more integrated and meaningful comparison across all depth levels. This combined approach enhances the analysis by highlighting the overall distribution and variation in technological proximity across the different levels, providing a clearer picture of the technological relationships within the consortia.

Blau's index technological proximity	
First quartile (Q1):	0.5878
Median (Q2):	0.6942
Third quartile (Q3):	0.7923

Table 4: Data distribution Blau's index technological proximity

The crisp set was determined by the median of 0.6942. Since a low Blau's index indicates high proximity, the binary variable is set to 1 if the data point is below the median. If the data point is above the median, it indicates low proximity and is set to 0.

Based on these thresholds, four categories were established to classify the data points for the fuzzy dataset. If a data point is smaller than the first quartile (Q1), it is categorized as 1. A value less than the second quartile (Q2) but greater than or equal to Q1 is assigned a category of 0.75. Similarly, a value less than the third quartile (Q3) but greater than or equal to Q2 is categorized as 0.25. All remaining data points, those greater than or equal to Q3, are classified as 0. This classification scheme avoids placing data points in the middle of the range, thereby enhancing the granularity of the representation compared to binary data while preventing ambiguity at the midpoint.

3.4 Validity and Reliability

Validity

In this research, various strategies were employed to achieve high validity.

Firstly, operational definitions were meticulously crafted for key success indicators such as created standards, standard adoption, and scholarly recognition. These definitions were grounded in specific inclusion and exclusion criteria. For instance, the success indicator "created standards" required documented evidence from official consortium publications or annual reports. This stringent requirement ensured that the measurement truly reflected the consortium's ability to develop formalized guidelines.

To further enhance validity, a comprehensive approach was adopted for determining the adoption of standards. This involved analyzing multiple sources and qualitative indicators from various websites and news articles. By triangulating data from these diverse sources, a more accurate and reliable measure of standard adoption was achieved, minimizing the risk of bias or incomplete information.

Another critical step in ensuring validity was the calibration of data into fuzzy sets and crisp sets. This process used theoretically and empirically justified thresholds, such as medians for categorizing Blau's index values. By doing so, the measures accurately captured varying degrees of proximity and influence among consortium members. The robustness of the methodological framework also contributed to the study's validity. The use of Fuzzy-Set Qualitative Comparative Analysis (fsQCA) allowed for a nuanced analysis of complex causal relationships. The meticulous calibration of variables and the logical minimization process provided a strong foundation for internal validity, ensuring that the findings as good as possible reflected the phenomena under investigation.

Reliability

Several measures were taken to ensure that the results of this study are reliable.

The data collection process was systematic and thoroughly documented. Explicit criteria for inclusion and exclusion were defined and adhered to throughout the research. This systematic approach ensures that the data collection process can be replicated by other researchers, yielding consistent results.

The analysis was conducted using the fs/QCA software developed by Ragin (2024), a well-established tool in the field of qualitative comparative analysis. The use of this standardized software enhances the reliability of the findings, as it provides a consistent platform for the analysis.

Transparency was a key aspect of the research. Every step of the data analysis, including the calculation of Blau's indices and the calibration of variables, was meticulously documented. The Excel files containing the raw data and intermediate calculations were made available, allowing for the verification and replication of the study by other researchers.

The calibration process was uniformly applied across all variables. Consistent thresholds, such as medians for Blau's indices, were used to transform raw data into fuzzy sets or crisp sets. This uniformity in calibration ensures that the data transformation process is reliable and can be replicated.

The methods used to calculate the Consortium Dominance Score (CDS) and measure geographical and technological proximity were clearly defined and based on replicable procedures. This clarity and consistency in methodology ensure that the same methods can be applied to different datasets, yielding reliable results.

In summary, by addressing both validity and reliability through systematic data collection, the use of established tools, transparent documentation, and consistent calibration procedures, this research ensures that its findings are both accurate and consistent. This solid foundation supports a deeper understanding of the factors influencing consortium success, providing valuable insights for future research and practical applications.

4 Results

The dataset analyzed in this study consists of 40 consortia within the Audio/Video/Multimedia sector, chosen from an initial pool of 138 identified consortia. These consortia were selected based on criteria such as relevance, data availability, and representativeness, ensuring a diverse and comprehensive sample. The selected consortia exhibit varying degrees of large company dominance, geographical proximity, and technological focus, providing a robust foundation for the Qualitative Comparative Analysis (QCA).

4.1 Truth Tables and Simplification

This section discusses the construction, simplification, and interpretation of truth tables in Qualitative Comparative Analysis. Truth tables are a fundamental tool in QCA, used to systematically display the presence or absence of conditions across different cases and their corresponding outcomes. The process of deriving and simplifying truth tables is crucial for identifying the key configurations of conditions that lead to a particular outcome, such as the success of consortia in the Audio/Video/Multimedia sector. The appendix 8 of this document contains detailed truth tables for each analysis conducted in this study, illustrating the presence and absence of conditions across different consortia and their corresponding outcomes.

Components of a Truth Table

A truth table consists of several rows, each representing a unique configuration of conditions, also known as causal paths or recipes. Each condition can either be present (1) or absent (0) in a configuration. The outcome, which in this study is the success indicator of consortia, can also be present (1) or absent (0). Additionally, truth tables include measures of consistency and coverage for each configuration. Consistency refers to the proportion of cases with the outcome that exhibit the combination of conditions, indicating the reliability of the configuration. Coverage indicates the proportion of cases with the outcome that are explained by a particular configuration, reflecting its explanatory power (Mendel & Korjani, 2012).

Interpretation of Truth Tables

Interpreting truth tables involves understanding the relationships between conditions and the outcome. High consistency and coverage values are indicative of strong and reliable pathways to the outcome. Consistency close to 1 means that the configuration reliably predicts the outcome, while high coverage means the configuration accounts for a large proportion of the outcome cases. For instance, a configuration with a (raw) consistency of 0.85 means 85% of cases with this configuration exhibit the outcome, and a coverage of 0.60 means this configuration explains 60% of all cases with the outcome. If we take a first glance at the truth tables (also added in appendix 8), we see a lot of possible solutions and outcomes with varying raw consistency and PRI consistency. The analysis of the binary truth tables reveals that they contain relatively low consistency and coverage scores. Specifically, the maximum consistency score in the binary truth table for high success is 0.5, and for moderate success, it is 0.75. In contrast, the scores for the fuzzy dataset truth tables are generally higher. The highest score for moderate success in the fuzzy truth table is 0.833, while for high success, it reaches 1.

CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	Dominance(>250)	Dominance(top10%)	number	Successindicator	cases	raw consist.	PRI consist.	SYM consist
0	0	1	0	0	1	1	0	3	1	cases	1	1	1
0	0	1	0	0	1	1	1	3	1	cases	1	1	1
0	0	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	1	1	1	1	0	1	1	cases	1	1	1
0	0	0	0	1	1	1	1	1	1	cases	1	1	1
0	1	1	1	1	1	1	1	1	1	cases	1	1	1
0	1	1	0	0	1	1	1	4	1	cases	0.75	0.75	0.75
0	1	1	0	1	1	1	1	3	0	cases	0.666667	0.666667	0.666667
0	1	1	0	0	1	0	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	0	1	1	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	0	1	1	2	0	cases	0.5	0.5	0.5
0	0	0	0	0	1	1	1	2	0	cases	0.5	0.5	0.5
0	0	1	0	1	1	1	1	2	0	cases	0.5	0.5	0.5
0	0	1	0	0	1	0	0	1	0	cases	0	0	0
0	1	1	0	1	1	0	0	1	0	cases	0	0	0
0	0	1	1	1	1	0	0	1	0	cases	0	0	0
0	1	1	1	1	1	0	0	1	0	cases	0	0	0
0	0	1	0	1	1	1	0	1	0	cases	0	0	0
1	1	1	1	1	1	0	1	1	0	cases	0	0	0
0	0	0	0	0	0	1	1	1	0	cases	0	0	0
1	1	1	0	1	1	1	1	1	0	cases	0	0	0

Figure 5: Truth table binary variable + moderate success

LCDcategorisation250	LCD_categorisationtop10	CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	number	Successindicator	cases	raw consist.	PRI consist.	SYM consist
0	1	0	1	1	0	1	1	1	1	cases	0.833333	0.833333	0.833333
1	0	0	1	1	1	1	1	1	0	cases	0.777778	0.777778	0.777778
0	1	0	1	1	0	0	0	1	0	cases	0.75	0.75	0.75
0	1	0	1	1	1	1	1	1	0	cases	0.727273	0.727273	0.727273
1	0	0	1	1	0	0	1	1	0	cases	0.705882	0.705882	0.705882
1	0	0	1	1	0	1	1	1	0	cases	0.705882	0.705882	0.705882
0	1	0	0	1	0	0	1	1	0	cases	0.6875	0.6875	0.6875
0	1	0	1	1	0	0	1	2	0	cases	0.666667	0.666667	0.666667
0	1	0	0	1	0	0	0	1	0	cases	0.666667	0.666667	0.666667
0	1	0	0	1	0	1	1	1	0	cases	0.666667	0.666667	0.666667
0	0	0	1	1	0	0	1	3	0	cases	0.653846	0.653846	0.653846
0	0	0	0	1	0	0	1	1	0	cases	0.65	0.65	0.65
0	0	0	1	1	0	1	1	2	0	cases	0.636364	0.636364	0.636364
1	0	0	0	1	0	0	1	1	0	cases	0.625	0.625	0.625
0	0	0	0	1	0	1	1	2	0	cases	0.6	0.6	0.6
0	0	0	0	0	0	1	1	1	0	cases	0.583333	0.583333	0.583333
0	0	0	1	1	0	0	0	2	0	cases	0.5625	0.5625	0.5625
1	1	0	0	1	0	0	1	4	0	cases	0.545455	0.545455	0.545455
1	0	0	0	0	0	0	1	2	0	cases	0.533333	0.533333	0.533333
1	1	0	1	1	0	0	1	2	0	cases	0.526316	0.526316	0.526316
1	1	0	1	1	0	1	1	2	0	cases	0.5	0.5	0.5
0	1	0	0	1	1	1	1	1	0	cases	0.5	0.5	0.5
1	1	0	0	1	1	1	1	2	0	cases	0.461538	0.461538	0.461538
1	1	0	1	1	1	1	1	1	0	cases	0.454545	0.454545	0.454545
1	0	0	0	0	0	0	0	1	0	cases	0.375	0.375	0.375
1	0	1	1	1	1	1	1	1	0	cases	0.2	0.2	0.2
1	0	1	1	1	0	1	1	1	0	cases	0.166667	0.166667	0.166667

Figure 6: Truth table categorial variable + moderate success

CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	Dominance(>250)	Dominance(top10%)	number	Highsuccessindicator	cases	raw consist.	PRI consist.	SYM consist
0	0	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	0	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	0	1	1	2	0	cases	0.5	0.5	0.5
0	1	1	0	1	1	1	1	3	0	cases	0.333333	0.333333	0.333333
0	1	1	0	0	1	1	1	4	0	cases	0.25	0.25	0.25
0	1	1	0	0	1	0	0	2	0	cases	0	0	0
0	0	1	0	0	1	0	0	1	0	cases	0	0	0
0	1	1	0	1	1	0	0	1	0	cases	0	0	0
0	0	1	1	1	1	0	0	1	0	cases	0	0	0
0	1	1	1	1	1	0	0	1	0	cases	0	0	0
0	0	1	0	0	1	1	0	3	0	cases	0	0	0
0	0	1	0	0	1	1	1	3	0	cases	0	0	0
0	1	1	0	0	1	1	0	2	0	cases	0	0	0
0	0	1	1	1	1	1	0	2	0	cases	0	0	0
0	0	0	0	0	1	1	1	2	0	cases	0	0	0
0	0	1	0	1	1	1	1	2	0	cases	0	0	0
0	1	1	0	0	0	1	0	1	0	cases	0	0	0
0	0	1	0	1	1	1	0	1	0	cases	0	0	0
0	1	1	1	1	1	1	0	1	0	cases	0	0	0
0	0	0	0	0	0	1	1	1	0	cases	0	0	0
0	0	0	0	1	1	1	1	1	0	cases	0	0	0
0	1	1	1	1	1	1	1	1	0	cases	0	0	0
1	1	1	1	1	1	0	1	1	0	cases	0	0	0
1	1	1	0	1	1	1	1	1	0	cases	0	0	0

Figure 7: Truth table binary variable + high success

LCDcategorisation250	LCD_categorisationtop10	CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	number	ghsuccessindicat	cases	raw consist.	PRI consist.	SYM consist
0	1	0	0	1	0	0	0	1	0	cases	0.333333	0.333333	0.333333
0	1	0	1	1	0	1	1	1	0	cases	0.277778	0.277778	0.277778
0	0	0	1	1	0	0	0	2	0	cases	0.1875	0.1875	0.1875
0	1	0	0	1	0	0	1	1	0	cases	0.1875	0.1875	0.1875
0	1	0	1	1	1	1	1	1	0	cases	0.181818	0.181818	0.181818
1	0	0	1	1	0	1	1	1	0	cases	0.176471	0.176471	0.176471
0	0	0	1	1	0	0	1	3	0	cases	0.153846	0.153846	0.153846
0	1	0	1	1	0	0	1	2	0	cases	0.142857	0.142857	0.142857
0	1	0	0	1	0	1	1	1	0	cases	0.133333	0.133333	0.133333
1	0	0	1	1	1	1	1	1	0	cases	0.111111	0.111111	0.111111
0	0	0	0	1	0	0	1	1	0	cases	0.1	0.1	0.1
0	1	0	0	1	1	1	1	1	0	cases	0.1	0.1	0.1
0	0	0	1	1	0	1	1	2	0	cases	0.0909091	0.0909091	0.0909091
1	1	0	1	1	1	1	1	1	0	cases	0.0909091	0.0909091	0.0909091
0	1	0	1	1	0	0	0	1	0	cases	0.0833333	0.0833333	0.0833333
0	0	0	0	0	0	1	1	1	0	cases	0.0833333	0.0833333	0.0833333
0	0	0	0	1	0	1	1	2	0	cases	0.05	0.05	0.05
1	1	0	1	1	0	1	1	2	0	cases	0.05	0.05	0.05
1	1	0	0	1	0	0	1	4	0	cases	0	0	0
1	0	0	0	0	0	0	1	2	0	cases	0	0	0
1	1	0	1	1	0	0	1	2	0	cases	0	0	0
1	1	0	0	1	1	1	1	2	0	cases	0	0	0
1	0	0	0	0	0	0	0	1	0	cases	0	0	0
1	0	0	0	1	0	0	1	1	0	cases	0	0	0
1	0	0	1	1	0	0	1	1	0	cases	0	0	0
1	0	1	1	1	0	1	1	1	0	cases	0	0	0
1	0	1	1	1	1	1	1	1	0	cases	0	0	0

Figure 8: Truth table categorial variable + high success

However, interpreting relationships within a large overview like a truth table can be challenging. Therefore, truth tables are minimized to highlight the most frequently occurring and most predictive cases. This minimization process aids in focusing on the key configurations that best explain the outcomes, thus enhancing the interpretability and practical utility of the analysis.

Minimized truth tables

The minimization of truth tables in fsQCA, uses the Quine-McCluskey algorithm. This simplifies complex data by generating and selecting prime implicants—combinations of causal conditions that explain outcomes. It involves creating a prime implicant chart to visualize necessary conditions, selecting essential implicants that uniquely cover outcomes, and evaluating their coverage and consistency. The essential implicants are then combined to derive the simplest Boolean expression that explains the data. This process reduces data complexity, enhances interpretability, and focuses on the most impactful causal configurations, providing clear insights into the factors influencing consortium success. The outcome is three solutions per truth table:

- Complex Solution: This includes all possible configurations without any logical reduction, retaining the most detail and representing all observed combinations that lead to the outcome.
- Intermediate Solution: This solution simplifies the complex solution by incorporating theoretical and substantive knowledge, making logical assumptions about the relationships between conditions. It eliminates configurations that are logically redundant or unsupported by empirical data.
- Parsimonious Solution: The most simplified model, identifying only the essential conditions necessary to explain the outcome. It retains the highest explanatory power with the least complexity.

After minimizing the truth tables and reviewing the results, it is evident that most of the solutions consist of a combination of individual solutions. These individual solutions each exhibit low raw coverage and consistency scores but together achieve a combined consistency score above the threshold of 0.8. These aggregated patterns yield limited insights due to the contradictory nature of the paths. The insightful solutions with high raw coverage and relatively high consistency are the following two.:

Solution 1: Fuzzy Data Set with Moderate Success Outcome The Qualitative Comparative Analysis (QCA) of the fuzzy data set provides insightful results regarding the conditions that lead to moderate success. The analysis identifies a specific combination of factors that are sufficient for achieving this outcome. The pathway identified is:

Solution 1:

~LCDcategorisation250 * LCD_categorisationtop10 * Country * ~Sub-Industries * IndustryGroup

Figure 9: solution 1

In the results, specific notations are used to represent the presence or absence of variables and their relationships. The symbol ” ” indicates the absence of a particular condition , while the ”*” symbol represents the logical ”and,” signifying the combination of conditions within the solutions.

This combination includes the presence of large company dominance based on the top 10% (LCDcategorisationtop10), geographical proximity at the country level (Country), and technological proximity at the industry group level (IndustryGroup). Additionally, it involves the absence of large company dominance based on a headcount of more than 250 employees (LCDcategorisation250) and the absence of proximity at the sub-industry level (Sub-Industries).

The consistency of this solution is 0.833333, indicating that in 83.3% of the cases, this combination of conditions results in moderate success. The coverage of 0.163043 means that this combination explains 16.3% of all instances where moderate success is predicted. This level of coverage is reasonable given the numerous possible combinations and solutions in the analysis.

Further examination reveals that there are 32 cases with a membership score of 0.75 for this specific combination of conditions. This indicates a substantial number of instances where these factors come together to produce the desired outcome of moderate success.

The analysis of the binary data set reveals two primary pathways that lead to moderate success. Together, these pathways achieve a high overall consistency of 0.929 and a raw coverage of 0.565, indicating their significant explanatory power. The pathway identified are:

Solution 2:

UNGeoschemeSubregion * IndustryGroup * Sector * Dominance(top10%)

~Country * UNGeoschemeSubregion * ~IndustryGroup * Dominance(>250)

Figure 10: Solution 2

The Qualitative Comparative Analysis (QCA) of the dataset reveals two primary pathways that lead to moderate success, each characterized by a specific combination of conditions.

First Pathway: Moderate Success with High Certainty

The first pathway, with a consistency of 0.857143, signifies that it correctly predicts moderate success in 85.7% of the relevant cases. This pathway is characterized by a combination of geographical proximity at the UN subregion level (UNGeoschemeSubregion), technological proximity at both the industry group level (IndustryGroup) and sector level (Sector), and large company dominance based on the top 10

In this pathway, the analysis suggests that technological proximity should align at a broader industry group level rather than being too specific. This indicates that while diverse insights from varying sub-industries are beneficial, the level of specificity must be such that members can still effectively understand each other's substantial information. Furthermore, geographical proximity at the national level must be present, highlighting that companies collaborate best when they are located within the same or nearby UN subregions. This proximity facilitates better communication and trust-building, which are crucial for effective collaboration.

Additionally, the pathway shows the absence of large company dominance based on headcount but the presence of top 10% dominance. Although this might seem contradictory at first, it reflects a logical explanation: when primarily smaller companies constitute a consortium, there will be no large company dominance based on headcount. However, if dominance is assessed relative to the top 10

Second Pathway: High Success with Perfect Consistency

The second pathway indicates a perfect consistency score of 1, demonstrating its perfect alignment with the desired outcome of moderate success. This pathway is characterized by the absence of geographical proximity at the country level (Country), the presence of geographical proximity at the UN subregion level (UNGeoschemeSubregion), the absence of technological proximity at the industry group level (IndustryGroup), and the presence of large company dominance based on a headcount of more than 250 employees (Dominance(250)). This combination is present in two cases with a membership score of 1.

From this solution, it is clear that large company dominance is a crucial factor, significantly enhancing the consortium's ability to achieve high success. Large companies bring substantial resources, extensive networks, and significant influence, which are vital for driving the consortium's initiatives forward effectively. Additionally, geographical proximity at the UN subregion level is essential, facilitating better communication, frequent face-to-face interactions, and stronger trust among members, which are critical for efficient collaboration and decision-making. Lastly, technological proximity at the industry group level suggests that consortium members should share a similar technological base within the broader industry group, ensuring effective collaboration on technical aspects, fostering innovation, and problem-solving.

The QCA results from both the fuzzy and binary data sets reveal specific combinations of conditions that lead to moderate and high success. These pathways highlight the crucial roles of geographical and technological proximities, as well as the dominance of large companies, in predicting successful outcomes. The high consistency and coverage values of these solutions underscore their robustness and reliability in explaining the conditions leading to success. These findings provide a solid foundation for understanding the factors contributing to success and can be valuable for strategic planning and decision-making in related fields.

4.2 Necessary and sufficient conditions

This subsection includes the analysis of the necessary conditions for achieving success, we examined both moderate and high success indicators using fuzzy and binary data sets. The necessity table are presented in appendix 10. A necessity table is used in qualitative comparative analysis (QCA) to determine if certain conditions are necessary for an outcome to occur. In other words, it assesses whether a particular condition must be present for the outcome to be achieved.The results reveal intriguing patterns and overlaps that reinforce the validity of our solution pathways. Here, we delve into the significant findings and their alignment with our identified pathways.

UNGeoschemeSubregion, which means geographical proximity on United Nations geoscheme subregion level, emerges as a pivotal condition across all scenarios. Its consistency values are notably high: 0.836957 for moderate success in the fuzzy data set, 0.913043 in the binary data set, 1.000000 for high success in the binary data set, and 0.900000 in the fuzzy data set. This indicates that geographical proximity at the UN subregion level consistently contributes to both moderate and high success outcomes. This strong alignment underscores the critical role of regional proximity in fostering successful collaborations and outcomes.

- Necessity: The condition demonstrates high consistency across all scenarios, indicating it is a necessary condition for both moderate and high success. Specifically, its consistency values are 0.836957 (moderate success/fuzzy data set), 0.913043 (moderate success/binary data set), 1.000000 (high success/binary data set), and 0.900000 (high success/fuzzy data set).
- Sufficiency: Given its high consistency and the role it plays in the solution pathways, UNGeoschemeSubregion is also a sufficient condition for success. Its strong alignment with successful outcomes highlights its dual role as both necessary and sufficient.

Sector, which means technological proximity on sector level, demonstrates high consistency in achieving moderate success. This is indicated by consistency values of 0.804348 in the fuzzy data set and 0.869565 in the binary data set. However, its influence wanes slightly in the context of high success, suggesting that while sectoral proximity is crucial for moderate success, other factors may take precedence for higher levels of achievement. This highlights the importance of industry-specific dynamics in driving moderate success outcomes.

- Necessity: The sector condition exhibits high consistency for moderate success with values of 0.804348 (fuzzy data set) and 0.869565 (binary data set), indicating it is necessary for moderate success.
- Sufficiency: The lower consistency for high success (e.g., 0.600000) suggests that while sector proximity is necessary for moderate success, it is not a sufficient condition for high success alone. Other factors must complement it to achieve higher success levels.

Dominance by Large Companies (both top 10% and 250 employees) is another condition that stands out. Dominance based on the measuring method top 10% , shows moderate consistency across all scenarios, while dominance measured by companies with more than 250 employees exhibits extremely high consistency in the binary data set, with values of 0.956522 for moderate success and 1.0 for high success. This indicates that the presence of large, dominant companies is a strong predictor of success, especially when measured by binary indicators. The dominance condition's high consistency aligns well with the identified solution pathways, reinforcing the idea that large companies play a crucial role in driving successful outcomes.

Dominance by Large Companies (250 employees)

- Necessity: Dominance by companies with more than 250 employees shows extremely high consistency in the binary data set for both moderate (0.956522) and high success (1.0), making it a necessary condition for success.
- Sufficiency: Given the perfect consistency for high success in the binary data set, this condition is also sufficient for achieving high success, particularly when large company dominance is a decisive factor.

Dominance by Large Companies (top 10%)

- Necessity: This condition has moderate consistency across all scenarios, indicating it is a necessary condition but not as strongly as the 250 employees criterion.
- Sufficiency: The presence of large company dominance based on the top 10% is not sufficient alone for high success, as indicated by its lower consistency for high success compared to the 250 employees criterion.

Country-Level Proximity, which means geographical proximity on country level,is another significant factor with moderate to high consistency values across all scenarios. Its consistency values are 0.554348 for moderate success in the fuzzy data set, 0.521739 in the binary data set, 0.800000 for high success in the binary data set, and 0.700000 in the fuzzy data set. This suggests that geographical proximity at the country level is an important but not overwhelmingly decisive factor compared to regional proximity at the UN subregion level.

- Necessity: The consistency values (0.554348 for moderate success/fuzzy data set, 0.521739 for moderate success/binary data set, 0.800000 for high success/binary data set, and 0.700000 for high success/fuzzy data set) indicate that country-level proximity is a necessary condition.
- Sufficiency: However, the moderate consistency values suggest that country-level proximity alone is not sufficient to achieve success. It must be combined with other conditions.

Conversely, **CityHeadquarters**, which means geographical proximity city level, consistently shows zero consistency and coverage across all success indicators. This indicates that the location of company headquarters at the city level is not a significant condition for achieving either moderate or high success. This contrasts with the importance of broader geographical proximities and suggests that more localized proximities may not be as influential.

- Necessity: This condition consistently shows zero consistency and coverage across all success indicators, indicating it is neither necessary nor sufficient for achieving success.
- Sufficiency: Given its lack of influence, city-level headquarters location is not a sufficient condition for success in any scenario.

Sub-Industries (Technological proximity measured on subindustry level)

- Necessity: The consistency values for sub-industries are relatively low across all scenarios, indicating it is not a strong necessary condition. Specifically, the values are 0.163043 (moderate success/fuzzy data set), 0.130435 (moderate success/binary data set), 0.000000 (high success/binary data set), and 0.100000 (high success/fuzzy data set). This suggests that sub-industry proximity does not play a significant role in achieving success.

- Sufficiency: The low consistency values also indicate that sub-industry proximity alone is not sufficient to achieve success. It is neither necessary nor sufficient, playing a minor role in the overall success outcomes.

IndustryGroup (Technological proximity measured on industry group level)

- Necessity: The consistency values for industry group proximity are moderate, indicating it is not a strong necessary condition. The values are 0.402174 (moderate success/fuzzy data set), 0.347826 (moderate success/binary data set), 0.400000 (high success/binary data set), and 0.400000 (high success/fuzzy data set). This implies that industry group proximity has some relevance but is not a decisive factor on its own.
- Sufficiency: The moderate consistency values suggest that industry group proximity is not sufficient on its own to achieve success. It must be combined with other conditions to significantly influence success outcomes.

4.3 Key finding

4.3.1 Variables

An examination of the necessity tables reveals critical factors for the success of consortia in the Audio/Video/Multimedia sector. These findings provide valuable insights for enhancing strategic planning and decision-making:

Geographical Proximity at the UN Subregion Level

The analysis reveals that geographical proximity at the UN subregion level consistently emerges as a pivotal condition for both moderate and high success. For moderate success, the consistency values are notably high across both fuzzy and binary datasets, such as 0.836957 in the fuzzy dataset and 0.913043 in the binary dataset. For high success, this condition achieves a perfect consistency value of 1.0 in the binary dataset . These findings suggest that consortia benefit significantly from having members located within the same regional proximity, which likely enhances communication, trust-building, and collaborative efficiency .

Large Company Dominance

The presence of large companies within a consortium, measured either by inclusion in the top 10% of companies or having more than 250 employees, shows varying levels of influence on success. For moderate success, large company dominance based on having more than 250 employees displays a high consistency value of 0.956522 in the binary dataset, indicating its near-necessity. For high success, the condition is even more critical, with a perfect consistency value of 1.0 in the binary dataset. This indicates that the presence of large companies is both a necessary and sufficient condition for achieving high success, highlighting their vital role in the consortium's outcomes .

Technological Proximity at the Industry Group Level

Technological proximity at the industry group level demonstrates moderate consistency values, such as 0.402174 for moderate success in the fuzzy dataset. This indicates that while technological proximity is relevant, it is not a decisive factor on its own. It must be combined with other conditions to significantly influence success outcomes. This suggests that while shared technological expertise is beneficial, it must be complemented by other factors to drive consortium success .

Sector Proximity

Sector proximity exhibits high consistency for achieving moderate success, with values like 0.804348 in the fuzzy dataset. However, its influence diminishes for high success, indicating that while sectoral proximity is important for moderate success, other factors may take precedence for achieving higher levels of success .

Real-Life Context and Implications

Regional Collaboration

Consortia should prioritize including members from at least the same UN subregion to maximize their chances of success. The regional proximity facilitates better communication, trust-building, and resource sharing, which are crucial for effective collaboration. The findings suggest that geographical proximity is a key factor in both moderate and high success, underscoring the importance of regional collaboration .

Leverage Large Companies

The presence of large companies within a consortium significantly enhances the likelihood of success. Consortia should therefore strategically include such entities. Large companies contribute financial stability, extensive resources, and substantial influence, which can drive the consortium's initiatives more effectively. The perfect consistency value for high success highlights the necessity of large company dominance in achieving significant outcomes .

Balanced Technological Diversity

While technological proximity at the industry group level is relevant, a balance must be struck to avoid the pitfalls of excessive similarity. Too much similarity can stifle innovation, while too much diversity can hinder effective collaboration. A balanced approach ensures efficient communication and fosters innovative problem-solving. Consortia should aim to include members with complementary technological expertise to enhance their innovative capabilities .

Sector-Specific Strategies

Sector proximity is crucial for moderate success, indicating that consortia should adopt sector-specific strategies and collaborations. Understanding the dynamics and specific needs of the sector can help consortia tailor their initiatives to address industry-specific challenges effectively. This targeted approach can enhance the relevance and impact of the consortium's work within the sector

4.3.2 Hypothesis findings

The necessary condition analysis conducted in this study confirms or denies the following hypotheses:

Hypothesis 1: The dominance of large companies within a consortium is a key factor influencing its success. Confirmed: The analysis shows that large company dominance has high consistency across both moderate and high success indicators. For instance, the consistency value of 1.0 for high success confirms the critical role of large companies in consortium success

Hypothesis 2: Geographical proximity among consortium members is a key factor influencing the success of the consortium.

Confirmed: Geographical proximity at the UN subregion level consistently contributes to both moderate and high success, as evidenced by high consistency values such as 1.0 for high success in the binary dataset. This underscores the importance of regional collaboration.

Hypothesis 3: The success of a consortium is influenced by the level of technological proximity among its members.

Partially Confirmed: Technological proximity at the industry group level shows moderate consistency values, indicating it is relevant but not decisive on its own. It needs to be combined with other conditions to significantly influence success outcomes.

Hypothesis 4: The success of a consortium is determined by specific configurations of

large company dominance, geographic proximity, and technological proximity.

Confirmed: The combined analysis reveals that specific configurations of these factors significantly influence success. For example, the pathway combining large company dominance and geographical proximity at the UN subregion level consistently leads to high success, demonstrating the importance of these combined factors.

In conclusion, the QCA solutions highlight the critical importance of geographical and technological proximities, as well as large company dominance, in achieving success in consortia. These findings provide a robust foundation for strategic planning, emphasizing the need for regional collaboration, leveraging large companies, balancing technological diversity, and adopting sector-specific strategies. These insights can guide consortia in enhancing their collaborative efforts and achieving successful outcomes in the Audio/Video/Multimedia sector.

5 Conclusion

This research investigated the dynamics of standard-setting consortia within the Audio/Video/Multimedia sector, focusing on the roles of large company dominance, geographical proximity, and technological proximity. The study revealed that large company dominance significantly influences consortium success, but an optimal balance is crucial to avoid power struggles and ensure effective collaboration. Geographical proximity, especially at the UN subregion level, was found to consistently contribute to consortium success by facilitating trust and communication. Technological proximity within industry groups also plays a beneficial role, although it must be complemented by other factors to significantly impact outcomes. The success of consortia is best understood through specific configurations of these variables rather than any single factor alone.

The primary research question addressed in this study was: "What combinations of large company dominance, geographic proximity, and technological proximity lead to successful outcomes in standard-setting consortia?". The findings indicate that successful consortia are characterized by balanced large company influence, significant geographical proximity, and appropriate technological alignment. While each factor individually contributes to success, their combined effects create the most favorable outcomes. The study also highlighted the importance of managing large company dominance to avoid monopolization and fostering inclusive collaboration among all members.

This research contributes to the field by providing empirical evidence on the strategic influence of large companies within standard-setting consortia, particularly in the Audio/Video/Multimedia sector. It extends the understanding of how large firms drive innovation while balancing the contributions of smaller participants. The study also offers nuanced insights into the roles of geographical and technological proximities, emphasizing their combined effects on consortium success. By highlighting the need for balanced configurations and the interplay of various factors, this research enriches the academic discourse on standardization and collaborative innovation.

From a Management of Technology perspective, this thesis demonstrates how strategic engagement in standard-setting consortia can enhance a firm's technological capabilities and market positioning. Technology managers can use these insights to navigate standard-setting processes more effectively, ensuring that their firms leverage the benefits of collaboration while maintaining an optimal balance of influence. Policymakers should consider developing guidelines that promote balanced representation within consortia, fostering environments where smaller firms can contribute meaningfully. This approach can enhance the overall innovation capacity of consortia and ensure that standards reflect a broader range of industry needs. For industry practitioners, understanding the critical roles of geographical and technological proximities can help in forming strategic partnerships and collaborations. Emphasizing regional collaboration and aligning technological interests can drive more effective and innovative outcomes. By integrating these findings into technological and managerial strategies, firms can better manage their participation in standard-setting consortia, ultimately enhancing their innovation capabilities and market success.

In summary, this research offers valuable insights into the dynamics of standard-setting consortia, providing a framework for understanding the factors that drive successful collaboration and innovation. These findings contribute to both theoretical knowledge and practical applications, informing technology management practices and shaping policies that support effective standard-setting efforts.

6 Discussion

The Qualitative Comparative Analysis (QCA) conducted in this study has yielded insightful findings regarding the pathways leading to both moderate and high success among consortia in the Audio/Video/Multimedia sector. These results provide valuable implications for strategic planning and decision-making within such consortia. This study addresses several gaps identified in the literature review. It provides empirical evidence on the strategic influence of large companies within consortia, particularly in the Audio/Video/Multimedia sector, a topic that was previously underexplored. By highlighting the combined effects of geographical and technological proximities, this research offers a more nuanced understanding of how these factors interact to influence consortium success. Furthermore, the study contributes to the discourse on power dynamics within consortia, offering insights into how dominance by large firms can be both a benefit and a hindrance, depending on how it is managed. This addresses a critical gap in understanding the balance needed for effective consortium collaboration.

6.1 Contextualizing Results within the Existing Literature

The findings of this study reveal significant insights when compared to existing literature, enriching our understanding of the dynamics within standard-setting consortia.

Firstly, the role of large company dominance was confirmed as a crucial factor influencing consortium success. This observation supports the assertions made by Schilling and Phelps (2007), who noted that large firms often shape the strategic direction and outcomes of consortia due to their extensive resources and market influence. However, our study also underscored the necessity of balance. Excessive dominance by large companies can lead to power struggles, potentially stifling the consortium's overall effectiveness. This insight resonates with Bouncken et al. (2015), who emphasized the risks of monopolization by large firms and the need to maintain collaborative dynamics within consortia.

Regarding geographical proximity, our analysis indicated that proximity at the UN subregion level consistently contributes to both moderate and high success in consortia. This finding is in line with the work of Hagedoorn et al. (2000), who highlighted the benefits of regional collaboration, including enhanced trust and more effective communication. Moreover, Balland and colleagues pointed out that proximity facilitates the transfer of tacit knowledge, which is crucial for innovation and successful collaboration in standard-setting activities.The role of technological proximity was partially confirmed in our study. While technological alignment within industry groups was found to be beneficial, it was not decisive on its own. This aligns with the observations of Cameron, Proudman, and Redding (2005), who suggested that while technological proximity can ease collaboration and foster innovation, it must be complemented by other factors to significantly impact outcomes. Additionally, the findings reflect Santamaría, Nieto, and Barge-Gil's emphasis on the importance of non-formal R&D activities and diverse technological inputs for successful innovation.

Importantly, the success of consortia was found to be determined by specific configurations of large company dominance, geographic proximity, and technological proximity. This holistic perspective is supported by Raab et al. (2013), who posited that the interplay of various factors is critical to the success of collaborative ventures. Our study reinforces this view, demonstrating that high success rates are achieved through particular combinations of these variables rather than the presence of any single factor alone. This study also addresses notable gaps in existing literature by providing empirical evidence on the strategic influence of large companies within standard-setting consortia, particularly in the Audio/Video/Multimedia sector. It extends our understanding of how large firms can drive innovation while balancing the contributions of smaller participants. Furthermore, by emphasizing the combined effects of geographical and technological proximities, the study offers a nuanced perspective that enriches existing literature and provides practical insights for forming and managing successful consortia.

In summary, the findings of this study align with and expand upon existing literature, underscoring the importance of large company dominance, geographical proximity, and technological alignment in achieving consortium success. By highlighting the need for balanced configurations and the interplay of various factors, this research contributes to a deeper understanding of consortium dynamics within the standard-setting landscape.

6.2 Implications for Theory and Practice

Theoretical Implications

Here's a revised version without using hyphens:

The findings of this study align with the Resource-Based View by illustrating how large firms leverage their substantial resources, such as capital, technological expertise, and extensive networks, to exert significant influence over consortium outcomes. In the context of standard-setting consortia, large companies often utilize their resource advantages to shape the development and adoption of industry standards. This influence can manifest in several ways, including driving the consortium's strategic direction, prioritizing certain technologies or standards that align with their business objectives, and ensuring that the final outputs are favorable to their market position. By doing so, these firms not only secure a competitive advantage within the consortium but also position themselves to benefit disproportionately from the standards once they are adopted across the industry. This strategic use of resources underscores the RBV's assertion that a firm's internal capabilities and assets are central to its ability to influence external environments and achieve sustained competitive advantage. The results also extend network theory by showing how geographic and technological proximities facilitate collaboration and innovation within consortia. However, the necessity for balance in large company dominance introduces a nuanced challenge to stakeholder theory, emphasizing the need for equitable participation and power distribution. These results challenge the simplistic view that larger firms' dominance is inherently beneficial, suggesting instead that optimal consortium performance depends on a balanced approach. This highlights the importance of considering power dynamics and the interplay of multiple factors in theoretical models of consortium success.

Practical Implications

For industry practitioners, these findings underscore the importance of managing large company dominance to avoid power imbalances that could stifle innovation. Ensuring equitable participation among all consortium members can enhance collaborative efforts and lead to more effective standard-setting. This can be achieved by establishing governance structures that promote equal decision-making opportunities, such as rotating leadership roles and ensuring that all members, regardless of size, have a voice in key decisions. Additionally, fostering transparent communication and creating clear guidelines for participation can help prevent any single entity from exerting disproportionate influence. By implementing these measures, consortia can maintain a balanced power dynamic that encourages innovation and ensures that the standards developed are reflective of the diverse interests within the group. Policymakers can use these insights to develop guidelines that promote balanced representation within consortia, fostering environments where smaller firms can contribute meaningfully. This approach can enhance the overall innovation capacity of consortia and ensure that standards reflect a broader range of industry needs. For other stakeholders, understanding the critical roles of geographical and technological proximities can help in forming strategic partnerships and collaborations. Emphasizing regional collaboration and aligning technological interests can drive more effective and innovative outcomes.

Academic Contributions

This research advances the existing body of knowledge by providing a detailed analysis of the factors influencing standard-setting consortia's success. It challenges and extends current theories by introducing the importance of balance in large company dominance and the interplay of various factors. These findings pave the way for future academic work to explore these dynamics in other sectors and contexts.The implications for the broader field include a deeper understanding of how consortia operate and the conditions that lead to their success. This study's holistic approach offers a framework that can be adapted and applied to other collaborative innovation settings, thereby enriching the academic discourse on standardization and innovation.

Societal/Managerial Relevance

The societal and managerial implications of these findings are significant. For managers, the insights on balancing power dynamics within consortia can lead to more effective governance and better innovation outcomes. Ensuring that all members, regardless of size, have a voice can foster a more inclusive and productive collaborative environment. From a societal perspective, this research highlights the importance of inclusive innovation processes that consider the needs and contributions of smaller firms. By promoting balanced and equitable collaboration, consortia can develop standards that better serve the entire industry and society at large, driving technological progress and economic growth.

In conclusion, this study's findings offer valuable insights for both theory and practice, providing a comprehensive understanding of the factors that drive success in standard-setting consortia. These insights can inform future research, guide industry practices, and shape policies that promote more effective and inclusive innovation collaborations.

6.3 Limitations

While this study provides valuable insights into the dynamics of standard-setting consortia, several limitations must be acknowledged to ensure a balanced perspective.

One significant limitation is the sector-specific focus on the Audio/Video/Multimedia industry. Although this sector plays a critical role in technological innovation and consumer products, the findings may not be fully generalizable to other industries. Different sectors might operate under distinct regulatory environments, face varying levels of market competition, or prioritize different types of innovation, all of which could influence how consortia function and what drives their success. For instance, sectors such as healthcare or telecommunications may have different collaboration dynamics, where the regulatory landscape, the pace of technological change, or the critical nature of the standards being set could significantly alter the factors that contribute to successful outcomes. Additionally, the strategic interests and power dynamics among consortium members might differ across industries, leading to unique challenges and opportunities that were not captured in this study. Therefore, further research is necessary to validate these findings in diverse contexts, ensuring that the conclusions drawn here are applicable beyond the specific sector studied.

When conducting the data we relied on publicly available data from consortium websites and LinkedIn profiles, which presents certain constraints. This approach ensures broad coverage and systematic data gathering, but the variability in the detail and completeness of publicly available information could affect the accuracy of the findings. Some consortia might not fully disclose all relevant activities or outcomes, leading to potential biases in the analysis. Moreover, defining and measuring the success of consortia is inherently complex. This study employs a multifactor framework focusing on the creation of standards, their adoption, and scholarly recognition. While robust, this framework may not capture all dimensions of success, such as long-term impact, user satisfaction, or economic benefits, potentially overlooking other relevant aspects of consortium performance.

The measures of geographical and technological proximity, though insightful, are simplifications. Geographical proximity is assessed at the city, country, and UN subregion levels, while technological proximity is evaluated at the industry group level. These measures do not fully account for global collaboration dynamics facilitated by digital communication, nor do they capture the complete spectrum of cognitive and knowledge similarities between consortium members. More nuanced measures could enhance the understanding of these proximities' impacts.

Furthermore, cross-sectional nature of this study captures a snapshot of current conditions and relationships within consortia, but it does not account for changes over time. Evolving dynamics, shifting power balances, and the long-term impacts of standards are not considered. Longitudinal studies could provide deeper insights into how these factors influence consortium success over extended periods.

The measurement of large company dominance through the Combined Dominance Score (CDS) is innovative but comes with limitations. While comprehensive, the CDS formula may not fully capture all dimensions of influence, such as informal networks or strategic alliances that are less visible. Additionally, defining large companies based solely on employee count might overlook other significant attributes like revenue or market share.

In summary, while this study makes significant contributions to understanding the dynamics of standard-setting consortia, it is essential to consider these limitations. Addressing them in future research can enhance the robustness and applicability of the findings, providing a more comprehensive understanding of consortium success factors.

6.4 Suggestions for Future Research

Building on the insights and limitations of this study, future research should expand its scope to include a broader range of industries beyond the Audio/Video/Multimedia sector. As identified in the limitations, the sector-specific focus of this study may limit the generalizability of the findings. Therefore, examining standard-setting consortia in diverse fields such as healthcare, telecommunications, and renewable energy is essential. These sectors operate under different regulatory environments, market dynamics, and technological imperatives, which could reveal unique factors influencing consortium success. A cross-sectoral analysis would help determine whether the observed dynamics are consistent across different contexts or whether industry-specific factors play a more significant role, providing a more comprehensive understanding of collaborative innovation.

Additionally, the cross-sectional nature of this study, as noted in the limitations, captures only a snapshot of current conditions and relationships within consortia. To address this, future research should conduct longitudinal studies that track changes in power balances, member contributions, and the long-term impacts of standards. Understanding how these dynamics evolve over time is crucial for developing strategies that ensure sustained success and adaptability. Longitudinal research could also explore how consortia adapt to new technological developments and market conditions, offering valuable lessons for future collaborations and helping to refine strategies for effective standard-setting efforts.

The limitations of this study also highlighted the simplifications made in measuring geographical and technological proximity. Future research should aim to develop more nuanced measures that capture the full complexity of these proximities. For example, finer-grained analyses could consider the role of digital communication in reducing geographical barriers and explore more detailed classifications of technological capabilities. These refined measures would provide a deeper understanding of how proximity influences collaboration and innovation within consortia. Additionally, the Combined Dominance Score (CDS) could be further developed to include other factors such as revenue, market share, and informal networks, offering a more holistic view of large company influence and its impact on consortium dynamics.

Finally, it is essential to explore the experiences and contributions of smaller firms within consortia, a topic that was not fully addressed in this study. Understanding how smaller companies navigate and contribute to consortia dominated by larger firms can lead to strategies that enhance inclusivity and equity. This focus could amplify the voices and innovations of smaller participants, thereby improving the overall effectiveness of consortia. Furthermore, investigating how different governance models and regulatory frameworks affect collaboration and innovation can inform the development of policies that support effective standard-setting practices. Addressing these areas in future research will build on the findings of this study and contribute to a more nuanced and comprehensive understanding of the factors that drive successful collaboration and innovation in standard-setting efforts.

References

Balland, P.-A., Boschma, R., & Frenken, K. (2015). Proximity and innovation: From statics to dynamics. *Regional Studies*, *49*(6), 907-920. Retrieved from https://doi.org/10.1080/00343404.2014.883598 doi: 10.1080/00343404.2014.883598

Baron, J., Ménière, Y., & Pohlmann, T. (2014). Standards, consortia, and innovation. *International Journal of Industrial Organization*, *36*, 22-35. Retrieved from https://www.sciencedirect.com/science/article/pii/S0167718714000551 (Standards, Intellectual Property Innovation) doi: https://doi.org/10.1016/j.ijindorg.2014.05.004

Baron, J., & Pohlmann, T. (2013, 12). Who cooperates in standards consortia-rivals or complementors? *Journal of Competition Law and Economics*, *9*, 905-929. doi: 10.1093/joclec/nht034

Blind, K., Kenney, M., Leiponen, A., & Simcoe, T. (2023, 10). Standards and innovation: A review and introduction to the special issue. *Research Policy*, *52*. doi: 10.1016/j.respol.2023.104830

Boschma, R. (2005, 02). Proximity and innovation: A critical assessment. *Regional Studies*, *39*, 61-74. doi: 10.1080/0034340052000320887

Bouncken, R., Gast, J., Kraus, S., & Bogers, M. (2015, 07). Coopetition: A systematic review, synthesis, and future research directions. *Review of Managerial Science*, *9*, 9 (3), 577-601. doi: 10.1007/s11846-015-0168-6

Cameron, G., Proudman, J., & Redding, S. (2005). Technological convergence, rd, trade and productivity growth. *European Economic Review*, *49*(3), 775-807. Retrieved from https://www.sciencedirect.com/science/article/pii/S0014292103000709 doi: https://doi.org/10.1016/S0014-2921(03)00070-9

Choi, B., Raghu, T. S., Vinzé, A., & Dooley, K. J. (2019, 4). Effectiveness of standards consortia: Social network perspectives. *Information Systems Frontiers*, *21*, 405-416. doi: 10.1007/s10796-017-9759-x

Crilly, D., Zollo, M., & Hansen, M. (2012, 12). Faking it or muddling through? understanding decoupling in response to stakeholder pressures. *Academy of Management Journal*, *55*, 1429-1448. doi: 10.5465/amj.2010.0697

Das, T., & Teng, B.-S. (2000). A resource-based theory of strategic alliances. *Journal of Management*, *26*(1), 31-61. Retrieved from https://www.sciencedirect.com/science/article/pii/S0149206399000379 doi: https://doi.org/10.1016/S0149-2063(99)00037-9

Eisenhardt, K. M., & Schoonhoven, C. B. (1996, April). Resource-based View of Strategic Alliance Formation: Strategic and Social Effects in Entrepreneurial Firms. *Organization Science*, *7*(2), 136-150. doi: 10.1287/orsc.7.2.136

European Commission, Directorate-General for Internal Market, E., Industry, & SMEs. (2020). *User guide to the sme definition*. Publications Office. doi: doi/10.2873/255862

Fiss, P. (2011, 04). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*. doi: 10.5465/AMJ.2011.60263120

Freeman, R., Dmytriyev, S., & Phillips, R. (2021). Stakeholder theory and the resource-based view of the firm. *Journal of Management*, *47*, 1757 - 1770. doi: 10.1177/0149206321993576

Fukami, Y., & Shimizu, T. (2021, 11). Technology standardization for innovation: How google leverages an open digital platform. *Information (Switzerland)*, *12*. doi: 10.3390/info12110441

Gertler, M. (2003, 02). Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography*, *3*, 75-99. doi: 10.1093/jeg/3.1.75

Greckhamer, T., Misangyi, V., Elms, H., & Lacey, R. (2007, 11). Using qualitative comparative analysis in strategic management research: An examination of combinations of industry, corporate, and business-unit effects. *Organizational Research Methods - ORGAN RES METHODS*, *11*, 695-726. doi: 10.1177/1094428107302907

Gulati, R. (1998). Alliances and networks. *Strategic Management Journal*, *19*(4), 293–317. Retrieved 2024-08-13, from http://www.jstor.org/stable/3094067

Gulati, R., & Westphal, J. D. (1999). Cooperative or controlling? the effects of ceo-board relations and the content of interlocks on the formation of joint ventures. *Administrative Science Quarterly*, *44*(3), 473–506. doi: 10.2307/2666959

Hagedoorn, J., Link, A., & Vonortas, N. (2000, 02). Research partnerships. *Research Policy*, *29*, 567-586. doi: 10.1016/S0048-7333(99)00090-6

Hansen, T., & Mattes, J. (2018). Proximity and power in collaborative innovation projects. *Regional Studies*, *52*(1), 35-46. Retrieved from https://doi.org/10.1080/00343404.2016.1263387 doi: 10.1080/00343404.2016.1263387

Hawkins, K. (2023, 07). *Gics vs. icb stock classification: What's the difference?* Retrieved 2024-03-13, from https://www.investopedia.com/articles/stocks/08/global-industry-classification-industrial-classification-benchmark.asp#:~:text=Comparing%20ICB%20and%20GICS&text=With%20the%20ICB,%20companies%20doing,between%20discretionary%20spending%20and%20staples.

Hillman, A. J., Cannella, A. A., & Paetzold, R. L. (2000). The resource dependence role of corporate directors: Strategic adaptation of board composition in response to environmental change. *Journal of Management Studies*, *37*(2), 235–255. doi: 10.1111/1467-6486.00179

Jain, A., & Dubey, A. (2020). Graph database using data crawling. *2020 IEEE Pune Section International Conference (PuneCon)*, 17-21. doi: 10.1109/PuneCon50868.2020.9362465

Katz, J., & Martin, B. (1997, 02). What is research collaboration? *Research Policy*, *26*, 1-18. doi: 10.1016/S0048-7333(96)00917-1

Kogut, B. (1989). The stability of joint ventures: Reciprocity and competitive rivalry. *Journal of Industrial Economics*, *38*(2), 183-98. Retrieved from https://EconPapers.repec.org/RePEc:bla:jindec:v:38:y:1989:i:2:p:183-98

Lee, W. S., & Sohn, S. Y. (2018, 7). Effects of standardization on the evolution of information and communications technology. *Technological Forecasting and Social Change*, *132*, 308-317. doi: 10.1016/j.techfore.2018.02.016

Leiponen, A. (2008). Competing through cooperation: The organization of standard setting in wireless telecommunications. *Manag. Sci.*, *54*, 1904-1919. doi: 10.1287/mnsc.1080.0912

Lemley, M. A. (2002). Intellectual property rights and standard-setting organizations. *California Law Review*, *90*(6), 1889–1980. Retrieved 2024-03-14, from http://www.jstor.org/stable/3481437

Letaifa, S., & Rabeau, Y. (2013, 10). Too close to collaborate? how geographic proximity could impede entrepreneurship and innovation. *Journal of Business Research*, *66*, 2071-2078. doi: 10.1016/j.jbusres.2013.02.033

Marek, P., Titze, M., Fuhrmeister, C., & Blum, U. (2016). R&d collaborations and the role of proximity. *Regional Studies*, *51*(12), 1761-1773. Retrieved from https://doi.org/10.1080/00343404.2016.1242718 doi: 10.1080/00343404.2016.1242718

Mendel, J., & Korjani, M. (2012). Charles ragin's fuzzy set qualitative comparative analysis (fsqca) used for linguistic summarizations. *Inf. Sci.*, *202*, 1-23. doi: 10.1016/J.INS.2012.02.039

Mizruchi, M. S. (1996). What do interlocks do? an analysis, critique, and assessment of research on interlocking directorates. *Annual Review of Sociology*, *22*, 271–298. doi: 10.1146/annurev.soc.22.1.271

Molina-Morales, F., Garcia-Villaverde, P., & Requena, G. (2011, 12). Geographical and cognitive proximity effects on innovation performance in smes: A way through knowledge acquisition. *International Entrepreneurship and Management Journal*, *Article in press*. doi: 10.1007/s11365-011-0214-z

Moon, S., & Lee, H. (2021). The primary actors of technology standardization in the manufacturing industry. *IEEE Access*, *9*, 101886-101901. doi: 10.1109/ACCESS.2021.3097800

MSCI Inc. (2023, Jan). Retrieved 2024-03-13, from `https://www.msci.com/index/methodology/latest/GICS`

Pfeffer, J., & Salancik, G. R. (1978). *The external control of organizations: A resource dependence perspective*. New York: Harper & Row.

Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard business review*, *76 6*, 77-90. Retrieved 2024-03-10, from `https://hbr.org/1998/11/clusters-and-the-new-economics-of-competition`

Raab, J., Mannak, R. S., & Cambré, B. (2013, 08). Combining Structure, Governance, and Context: A Configurational Approach to Network Effectiveness. *Journal of Public Administration Research and Theory*, *25*(2), 479-511. Retrieved from `https://doi.org/10.1093/jopart/mut039` doi: 10.1093/jopart/mut039

Ragin, C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies.* Berkeley and Los Angeles: University of California Press.

Ragin, C. (2024). *fs/qca software.* `https://sites.socsci.uci.edu/~cragin/fsQCA/software.shtml`. (Accessed: 2024-06-27)

Ray, S., & Jones, A. (2003, 01). Manufacturing interoperability. In (Vol. 17, p. 535-540). doi: 10.1007/s10845-006-0037-x

Rihoux, B., & Marx, A. (2013). Qca, 25 years after "the comparative method". *Political Research Quarterly*, *66*, 167 - 235. doi: 10.1177/1065912912468269

Rihoux, B., & Ragin, C. C. (2009). *Configurational comparative methods: Qualitative comparative analysis (qca) and relletaifaated techniques* (Vol. 1-51). Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781452226569

Ring, P., & Ven, A. (1992, 10). Structuring cooperative relationship between organizations. *Strategic Management Journal*, *13*, 483 - 498. doi: 10.1002/smj.4250130702

Rohlfing, I. (2020). The choice between crisp and fuzzy sets in qualitative comparative analysis and the ambiguous consequences for finding consistent set relations. *Field Methods*, *32*, 75 - 88. doi: 10.1177/1525822X19896258

Scherngell, T., & Barber, M. (2009, 08). Spatial interaction modelling of cross-region rd collaborations: Empirical evidence from the 5th eu framework programme. *Papers in Regional Science*, *88*, 531-546. doi: 10.1111/j.1435-5957.2008.00215.x

Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Science*, *53*, 1113-1126. Retrieved from `https://`

www.jstor.org/stable/20122273 doi: 10.1287/mnsc.l060.0624

Simcoe, T. (2012). Standard setting committees: Consensus governance for shared technology platforms. *The American Economic Review*, *102*(1), 305–336. Retrieved 2024-03-14, from http://www.jstor.org/stable/41408776

Solanas, A., Selvam, R., Navarro, J., & Leiva, D. (2012, 12). Some common indices of group diversity: Upper boundaries. *Psychological reports*, *111*, 777-96. doi: 10.2466/01.09.21.PR0.111.6.777-796

Storper, M., & Venables, A. (2004, 08). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, *4*, 351-370. doi: 10.1093/jnlecg/lbh027

Teubner, L. K., Henkel, J., & Bekkers, R. (2021, 4). Industry consortia in mobile telecommunications standards setting: Purpose, organization and diversity. *Telecommunications Policy*, *45*. doi: 10.1016/j.telpol.2020.102059

Tsironis, G., Karagkouni, A., Dimitriou, D., & Tsagarakis, K. P. (2023). Mapping sustainable practices and concepts in the transportation ecosystem for the eu-27 countries, based on linkedin company profiles. *Frontiers in Sustainability*. doi: 10.3389/frsus.2023.1268575

United Nations Statistics Division. (2024). *Standard country or area codes for statistical use (m49).* https://unstats.un.org/unsd/methodology/m49/. (Accessed: 2024-06-27)

Zahra, S. A., & Pearce, J. A. (1989). Boards of directors and corporate financial performance: A review and integrative model. *Journal of Management*, *15*(2), 291–334. doi: 10.1177/014920638901500208

7 Calibrated Data set

Consortium ID	Dominance(>250)	Dominance (top 10%)	City	Country	UN Geoscheme Subregion	Sub-Industries	Industry Group	Sector	Success indicator	High success indicator
1	1	1	0	0	0	0	1	1	1	0
2	1	0	0	0	1	0	0	1	1	0
3	1	0	0	1	1	0	0	1	1	0
4	1	0	0	0	1	0	0	1	1	0
5	1	1	0	1	1	0	0	1	1	0
6	1	1	0	0	1	0	0	1	1	0
7	1	1	0	1	1	0	1	1	1	0
8	1	0	0	1	1	0	0	0	1	0
9	0	0	0	1	1	0	0	1	1	0
10	1	1	0	1	1	0	0	1	1	0
11	0	0	0	1	1	0	0	1	0	0
12	1	0	0	0	1	0	0	0	1	1
13	1	1	0	0	1	0	0	1	1	0
14	1	1	0	1	1	0	0	1	1	1
15	0	0	0	1	1	0	1	1	0	0
16	1	0	0	1	1	1	1	1	1	0
17	1	1	0	0	0	0	0	1	1	0
18	1	1	0	1	1	0	0	1	0	0
19	1	0	0	0	1	1	1	1	1	0
20	1	1	0	1	1	0	0	0	1	1
21	0	0	0	0	1	1	1	1	0	0
22	0	0	0	0	1	0	0	1	0	0
23	1	0	0	0	1	0	0	1	1	0
24	1	0	0	0	1	0	1	1	0	0
25	1	1	0	0	1	0	0	1	1	0
26	1	1	0	1	1	1	1	1	1	0
27	1	1	0	1	1	0	1	1	0	0
28	1	1	0	0	1	0	1	1	0	0
29	0	0	0	1	1	1	1	1	0	0
30	1	0	0	1	1	0	0	1	0	0
31	1	1	0	1	1	0	1	1	1	1
32	1	0	0	1	1	0	1	1	1	1
33	0	1	1	1	1	1	1	1	0	0
34	1	0	0	1	1	0	1	1	0	0
35	1	1	0	1	1	0	0	0	0	0
36	1	1	0	0	1	0	1	1	1	0
37	1	0	0	0	1	1	1	1	0	0
38	1	1	1	1	1	0	1	1	0	0
39	1	1	0	0	0	0	0	1	0	0
40	1	1	0	0	0	0	0	0	0	0

Figure 11: Calibrated binary dataset

Consortium ID	LCDcategorisation250	LCD_categorisationtop10	City Headquarters	Country	UN Geoscheme Subregion	Sub-Industries	Industry Group	Sector	Success indicator	High success indicator
1	0,25	0,25	0	0,25	0,25	0	0,75	1	1	0
2	0	0,75	0	0,25	1	0	0,25	0,75	1	0
3	0	1	0,25	1	1	0	0,25	0,75	1	0
4	1	0,75	0	0,25	0,75	0,25	0,25	1	1	0
5	0,75	0,25	0	1	1	0	0,25	0,75	1	0
6	0,75	0	0	0,25	0,75	0,25	0,25	0,75	1	0
7	0	0,25	0	0,75	1	0,25	0,75	1	1	0
8	0,25	0,75	0,25	1	1	0	0	0,25	1	0
9	1	0,75	0	1	1	0	0,25	0,75	1	0
10	0,25	0	0	0,75	0,75	0	0	0,75	1	0
11	1	1	0,25	0,75	1	0	0,25	1	0	0
12	0	1	0	0,25	0,75	0	0	0,25	1	1
13	0,75	0,75	0	0,25	1	0	0,25	0,75	1	0
14	0	0,25	0	0,75	0,75	0	0,25	1	1	1
15	1	0,75	0,25	0,75	1	0	1	1	0	0
16	0,25	0,75	0	0,75	1	0,75	1	1	1	0
17	1	0,25	0	0	0,25	0	0	0,75	1	0
18	0,25	0	0	0,75	0,75	0	0,25	0,75	0	0
19	0,75	1	0,25	0,25	0,75	0,75	1	1	1	0
20	0	0	0	0,75	1	0	0	0,25	1	1
21	1	1	0	0,25	0,75	0,75	0,75	1	0	0
22	1	1	0	0,25	0,75	0,25	0,25	0,75	0	0
23	0,75	1	0	0,25	0,75	0	0,25	0,75	1	0
24	0,25	0,75	0	0,25	0,75	0,25	0,75	1	0	0
25	0,25	0	0	0,25	1	0	0,25	1	1	0
26	0,75	0,25	0,25	0,75	0,75	0,75	0,75	1	1	0
27	0	0,25	0,25	1	1	0,25	0,75	1	0	0
28	0,25	0	0	0,25	0,75	0	0,75	0,75	0	0
29	1	0,75	0	0,75	0,75	1	1	1	0	0
30	0,25	1	0	0,75	1	0	0	0,75	0	0
31	0,75	0,25	0	1	1	0,25	1	1	1	1
32	0	1	0	0,75	1	0,25	0,75	1	1	1
33	1	0	1	1	1	1	1	1	0	0
34	0,75	0,75	0,25	0,75	1	0	0,75	0,75	0	0
35	0	0	0,25	0,75	0,75	0	0,25	0,25	0	0
36	0	0	0	0,25	0,75	0,25	0,75	1	1	0
37	0	1	0,25	0,25	1	1	1	1	0	0
38	1	0	1	1	1	0	0,75	0,75	0	0
39	0,75	0,25	0	0	0,25	0,25	0,25	1	0	0
40	0,75	0,25	0	0,25	0,25	0	0	0,25	0	0

Figure 12: Calibrated fuzzy dataset

8 Truth tables

CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	Dominance(>250)	Dominance(top10%)	number	Successindicator	cases	raw consist.	PRI consist.	SYM consist
0	0	1	0	0	1	1	0	3	1	cases	1	1	1
0	0	1	0	0	1	1	1	3	1	cases	1	1	1
0	0	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	1	1	1	1	0	1	1	cases	1	1	1
0	0	0	0	1	1	1	1	1	1	cases	1	1	1
0	1	1	1	1	1	1	1	1	1	cases	1	1	1
0	1	1	0	0	1	1	1	4	1	cases	0.75	0.75	0.75
0	1	1	0	1	1	1	1	3	0	cases	0.666667	0.666667	0.666667
0	1	1	0	0	1	0	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	0	1	1	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	0	1	1	2	0	cases	0.5	0.5	0.5
0	0	0	0	0	1	1	1	2	0	cases	0.5	0.5	0.5
0	0	1	0	1	1	1	1	2	0	cases	0.5	0.5	0.5
0	0	1	0	0	1	0	0	1	0	cases	0	0	0
0	1	1	0	1	1	0	0	1	0	cases	0	0	0
0	0	1	1	1	1	0	0	1	0	cases	0	0	0
0	1	1	1	1	1	0	0	1	0	cases	0	0	0
0	0	1	0	1	1	1	0	1	0	cases	0	0	0
1	1	1	1	1	1	0	1	1	0	cases	0	0	0
0	0	0	0	0	0	1	1	1	0	cases	0	0	0
1	1	1	0	1	1	1	1	1	0	cases	0	0	0

Figure 13: Truth table binary variable + moderate success

LCDcategorisation250	LCD_categorisationtop10	CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	number	Successindicator	cases	raw consist.	PRI consist.	SYM consist
0	1	0	1	1	0	1	1	1	1	cases	0.833333	0.833333	0.833333
1	0	0	1	1	1	1	1	1	0	cases	0.777778	0.777778	0.777778
0	1	0	1	1	0	0	0	1	0	cases	0.75	0.75	0.75
0	1	0	1	1	1	1	1	1	0	cases	0.727273	0.727273	0.727273
1	0	0	1	1	0	0	1	1	0	cases	0.705882	0.705882	0.705882
1	0	0	1	1	0	1	1	1	0	cases	0.705882	0.705882	0.705882
0	1	0	0	1	0	0	1	1	0	cases	0.6875	0.6875	0.6875
0	1	0	1	1	0	0	1	2	0	cases	0.666667	0.666667	0.666667
0	1	0	0	1	0	0	0	1	0	cases	0.666667	0.666667	0.666667
0	1	0	0	1	0	1	1	1	0	cases	0.666667	0.666667	0.666667
0	0	0	1	1	0	0	1	3	0	cases	0.653846	0.653846	0.653846
0	0	0	0	1	0	0	1	1	0	cases	0.65	0.65	0.65
0	0	0	1	1	0	1	1	2	0	cases	0.636364	0.636364	0.636364
1	0	0	0	1	0	0	1	1	0	cases	0.625	0.625	0.625
0	0	0	0	1	0	1	1	2	0	cases	0.6	0.6	0.6
0	0	0	0	0	0	1	1	1	0	cases	0.583333	0.583333	0.583333
0	0	0	1	1	0	0	0	2	0	cases	0.5625	0.5625	0.5625
1	1	0	0	1	0	0	1	4	0	cases	0.545455	0.545455	0.545455
1	0	0	0	0	0	0	1	2	0	cases	0.533333	0.533333	0.533333
1	1	0	1	1	0	0	1	2	0	cases	0.526316	0.526316	0.526316
1	1	0	1	1	0	1	1	2	0	cases	0.5	0.5	0.5
0	1	0	0	1	1	1	1	1	0	cases	0.5	0.5	0.5
1	1	0	0	1	1	1	1	2	0	cases	0.461538	0.461538	0.461538
1	1	0	1	1	1	1	1	1	0	cases	0.454545	0.454545	0.454545
1	0	0	0	0	0	0	0	1	0	cases	0.375	0.375	0.375
1	0	1	1	1	1	1	1	1	0	cases	0.2	0.2	0.2
1	0	1	1	1	0	1	1	1	0	cases	0.166667	0.166667	0.166667

Figure 14: Truth table categorial variable + moderate success

CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	Dominance(>250)	Dominance(top10%)	number	Highsuccessindicator	cases	raw consist.	PRI consist.	SYM consist
0	0	1	0	0	0	1	0	1	1	cases	1	1	1
0	1	1	0	1	1	1	0	2	0	cases	0.5	0.5	0.5
0	1	1	0	0	0	1	1	2	0	cases	0.5	0.5	0.5
0	1	1	0	1	1	1	1	3	0	cases	0.333333	0.333333	0.333333
0	1	1	0	0	1	1	1	4	0	cases	0.25	0.25	0.25
0	1	1	0	0	1	0	0	2	0	cases	0	0	0
0	0	1	0	0	1	0	0	1	0	cases	0	0	0
0	1	1	0	1	1	0	0	1	0	cases	0	0	0
0	0	1	1	1	1	0	0	1	0	cases	0	0	0
0	1	1	1	1	1	0	0	1	0	cases	0	0	0
0	0	1	0	0	1	1	0	3	0	cases	0	0	0
0	0	1	0	0	1	1	1	3	0	cases	0	0	0
0	1	1	0	0	1	1	0	2	0	cases	0	0	0
0	0	1	1	1	1	1	0	2	0	cases	0	0	0
0	0	0	0	0	1	1	1	2	0	cases	0	0	0
0	0	1	0	1	1	1	1	2	0	cases	0	0	0
0	1	1	0	0	0	1	0	1	0	cases	0	0	0
0	0	1	0	1	1	1	0	1	0	cases	0	0	0
0	1	1	1	1	1	1	0	1	0	cases	0	0	0
0	0	0	0	0	0	1	1	1	0	cases	0	0	0
0	0	0	0	1	1	1	1	1	0	cases	0	0	0
0	1	1	1	1	1	1	1	1	0	cases	0	0	0
1	1	1	1	1	1	0	1	1	0	cases	0	0	0
1	1	1	0	1	1	1	1	1	0	cases	0	0	0

Figure 15: Truth table binary variable + high success

LCDcategorisation250	LCD_categorisationtop10	CityHeadquarters	Country	UNGeoschemeSubregion	Sub-Industries	IndustryGroup	Sector	number	ghsuccessindicat	cases	raw consist.	PRI consist.	SYM consist
0	1	0	0	1	0	0	0	1	0	cases	0.333333	0.333333	0.333333
0	1	0	1	1	0	1	1	1	0	cases	0.277778	0.277778	0.277778
0	0	0	1	1	0	0	0	2	0	cases	0.1875	0.1875	0.1875
0	1	0	0	1	0	0	1	1	0	cases	0.1875	0.1875	0.1875
0	1	0	1	1	1	1	1	1	0	cases	0.181818	0.181818	0.181818
1	0	0	1	1	0	1	1	1	0	cases	0.176471	0.176471	0.176471
0	0	0	1	1	0	0	1	3	0	cases	0.153846	0.153846	0.153846
0	1	0	1	1	0	0	1	2	0	cases	0.142857	0.142857	0.142857
0	1	0	0	1	0	1	1	1	0	cases	0.133333	0.133333	0.133333
1	0	0	1	1	1	1	1	1	0	cases	0.111111	0.111111	0.111111
0	0	0	0	1	0	0	1	1	0	cases	0.1	0.1	0.1
0	1	0	0	1	1	1	1	1	0	cases	0.1	0.1	0.1
0	0	0	1	1	0	1	1	2	0	cases	0.0909091	0.0909091	0.0909091
1	1	0	1	1	1	1	1	1	0	cases	0.0909091	0.0909091	0.0909091
0	1	0	1	1	0	0	0	1	0	cases	0.0833333	0.0833333	0.0833333
0	0	0	0	0	0	1	1	1	0	cases	0.0833333	0.0833333	0.0833333
0	0	0	0	1	0	1	1	2	0	cases	0.05	0.05	0.05
1	1	0	1	1	0	1	1	2	0	cases	0.05	0.05	0.05
1	1	0	0	1	0	0	1	4	0	cases	0	0	0
1	0	0	0	0	0	0	1	2	0	cases	0	0	0
1	1	0	1	1	0	0	1	2	0	cases	0	0	0
1	1	0	0	1	1	1	1	2	0	cases	0	0	0
1	0	0	0	0	0	0	0	1	0	cases	0	0	0
1	0	0	0	1	0	0	1	1	0	cases	0	0	0
1	0	0	1	1	0	0	1	1	0	cases	0	0	0
1	0	1	1	1	0	1	1	1	0	cases	0	0	0
1	0	1	1	1	1	1	1	1	0	cases	0	0	0

Figure 16: Truth table categorial variable + high success

9 Minimized truth tables

```
File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Highsuccessindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 1
Assumptions:
                                                                                                              raw       unique
                                                                                                            coverage   coverage   consistency
                                                                                                           ---------- ---------- ----------
~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector     0.05       0.05       0.0833333
~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector      0.25       0.2        0.277778
LCDcategorisation250*~LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector       0.05       0          0.111111
solution coverage: 0.3
solution consistency: 0.206897


Cases with greater than 0.5 membership in term ~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector: 8 (0.75,0)
Cases with greater than 0.5 membership in term ~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector: 32 (0.75,1)
Cases with greater than 0.5 membership in term LCDcategorisation250*~LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector: 26 (0.75,0)
```

Figure 17: minimized truth table categorial data set + high success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Highsuccessindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 1
                                                                                                 raw       unique
                                                                                               coverage   coverage   consistency
                                                                                              ---------- ---------- ----------
~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%)     0.2        0.2        1
solution coverage: 0.2
solution consistency: 1


Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%): 12 (1,1)

*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Highsuccessindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 1
                                         raw       unique
                                       coverage   coverage   consistency
                                      ---------- ---------- ----------
~Country*~Sector*~Dominance(top10%)      0.2        0          1
~Country*UNGeoschemeSubregion*~Sector    0.2        0          1
solution coverage: 0.2
solution consistency: 1


Cases with greater than 0.5 membership in term ~Country*~Sector*~Dominance(top10%): 12 (1,1)
Cases with greater than 0.5 membership in term ~Country*UNGeoschemeSubregion*~Sector: 12 (1,1)

*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Highsuccessindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 1
Assumptions:
                                                                                                 raw       unique
                                                                                               coverage   coverage   consistency
                                                                                              ---------- ---------- ----------
~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%)     0.2        0.2        1
solution coverage: 0.2
solution consistency: 1


Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%): 12 (1,1)
```

Figure 18: minimized truth table binary data set + high success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Successindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.75
                                                                   raw       unique
                                                                 coverage   coverage   consistency
                                                                ---------- ---------- ----------
~Sector*~Dominance(top10%)                                       0.0869565  0.0434783  1
~UNGeoschemeSubregion*IndustryGroup                              0.0434783  0.0434783  1
Country*Sub-Industries*Dominance(>250)                           0.0869565  0.0869565  1
~Country*UNGeoschemeSubregion*~IndustryGroup*Dominance(>250)     0.304348   0.130435   1
UNGeoschemeSubregion*~IndustryGroup*Sector*Dominance(top10%)     0.26087    0.130435   0.857143
solution coverage: 0.608696
solution consistency: 0.933333


Cases with greater than 0.5 membership in term ~Sector*~Dominance(top10%): 8 (1,1),
  12 (1,1)
Cases with greater than 0.5 membership in term ~UNGeoschemeSubregion*IndustryGroup: 1 (1,1)
Cases with greater than 0.5 membership in term Country*Sub-Industries*Dominance(>250): 16 (1,1),
  26 (1,1)
Cases with greater than 0.5 membership in term ~Country*UNGeoschemeSubregion*~IndustryGroup*Dominance(>250): 2 (1,1),
  4 (1,1), 6 (1,1), 12 (1,1),
  13 (1,1), 23 (1,1), 25 (1,1)
Cases with greater than 0.5 membership in term UNGeoschemeSubregion*~IndustryGroup*Sector*Dominance(top10%): 5 (1,1),
  6 (1,1), 10 (1,1), 13 (1,1),
  14 (1,1), 18 (1,0), 25 (1,1)
```

Figure 19: minimized truth table binary data set + moderate success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Successindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.75
Assumptions:
                                                                                                              raw       unique
                                                                                                            coverage   coverage   consistency
                                                                                                           ---------- ---------- ----------
~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%)      0.0869565  0.0869565  1
~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)*Dominance(top10%)        0.26087    0.130435   0.857143
~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector*Dominance(>250)                    0.0869565  0.0869565  1
~CityHeadquarters*~Country*~UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector*Dominance(>250)*Dominance(top10%) 0.0434783  0.0434783  1
~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)                 0.26087    0.130435   1
solution coverage: 0.608696
solution consistency: 0.933333


Cases with greater than 0.5 membership in term ~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%): 8 (1,1),
  12 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)*Dominance(top10%): 5 (1,1),
  6 (1,1), 10 (1,1), 13 (1,1),
  14 (1,1), 18 (1,0), 25 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector*Dominance(>250): 16 (1,1),
  26 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*~UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector*Dominance(>250)*Dominance(top10%): 1 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250): 2 (1,1),
  4 (1,1), 6 (1,1), 13 (1,1),
  23 (1,1), 25 (1,1)
```

Figure 20: minimized truth table binary data set + moderate success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Successindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.75
                                                                                                              raw       unique
                                                                                                            coverage   coverage   consistency
                                                                                                           ---------- ---------- ----------
~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%)      0.0869565  0.0869565  1
~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)*Dominance(top10%)        0.26087    0.130435   0.857143
~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector*Dominance(>250)                    0.0869565  0.0869565  1
~CityHeadquarters*~Country*~UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector*Dominance(>250)*Dominance(top10%) 0.0434783  0.0434783  1
~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)                 0.26087    0.130435   1
solution coverage: 0.608696
solution consistency: 0.933333


Cases with greater than 0.5 membership in term ~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*~Sector*Dominance(>250)*~Dominance(top10%): 8 (1,1),
  12 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250)*Dominance(top10%): 5 (1,1),
  6 (1,1), 10 (1,1), 13 (1,1),
  14 (1,1), 18 (1,0), 25 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*Country*UNGeoschemeSubregion*Sub-Industries*IndustryGroup*Sector*Dominance(>250): 16 (1,1),
  26 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*~UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector*Dominance(>250)*Dominance(top10%): 1 (1,1)
Cases with greater than 0.5 membership in term ~CityHeadquarters*~Country*UNGeoschemeSubregion*~Sub-Industries*~IndustryGroup*Sector*Dominance(>250): 2 (1,1),
  4 (1,1), 6 (1,1), 13 (1,1),
  23 (1,1), 25 (1,1)
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/fsQCAinputv1.1.csv
Model: Successindicator = f(CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector, Dominance(>250), Dominance(top10%))
Algorithm: Quine-McCluskey
```

Figure 21: minimized truth table binary data set + moderate success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Successindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.833333
                                                                                                            raw       unique
                                                                                                          coverage    coverage   consistency
                                                                                                         ----------  ----------  ----------
~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector     0.163043    0.163043    0.833333
solution coverage: 0.163043
solution consistency: 0.833333


Cases with greater than 0.5 membership in term ~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector: 32 (0.75,1)
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Successindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey
```

Figure 22: minimized truth table categorial data set + moderate success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Successindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.833333
Assumptions:
                                                                                                            raw       unique
                                                                                                          coverage    coverage   consistency
                                                                                                         ----------  ----------  ----------
~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector     0.163043    0.163043    0.833333
solution coverage: 0.163043
solution consistency: 0.833333


Cases with greater than 0.5 membership in term ~LCDcategorisation250*LCD_categorisationtop10*~CityHeadquarters*Country*UNGeoschemeSubregion*~Sub-Industries*IndustryGroup*Sector: 32 (0.75,1)
```

Figure 23: minimized truth table categorial data set + moderate success

```
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Successindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.833333
                                                                                raw       unique
                                                                              coverage    coverage   consistency
                                                                             ----------  ----------  ----------
~LCDcategorisation250*LCD_categorisationtop10*Country*~Sub-Industries*IndustryGroup     0.163043    0.163043    0.833333
solution coverage: 0.163043
solution consistency: 0.833333


Cases with greater than 0.5 membership in term ~LCDcategorisation250*LCD_categorisationtop10*Country*~Sub-Industries*IndustryGroup: 32 (0.75,1)
*********************
*TRUTH TABLE ANALYSIS*
*********************

File:  C:/Users/fabia/OneDrive - Delft University of Technology/Thesis Interorganizational networks and standard dominance/data/fsQCA/inputcategorien.csv
Model: Successindicator = f(LCDcategorisation250, LCD_categorisationtop10, CityHeadquarters, Country, UNGeoschemeSubregion, Sub-Industries, IndustryGroup, Sector)
Algorithm: Quine-McCluskey
```

Figure 24: minimized truth table categorial data set + moderate success

10 Necessity tables

Analysis of Necessary Conditions

Outcome variable: Highsuccessindicator

Conditions tested:

	Consistency	Coverage
CityHeadquarters	0.000000	0.000000
Country	0.800000	0.181818
UNGeoschemeSubregion	1.000000	0.138889
Sub-Industries	0.000000	0.000000
IndustryGroup	0.400000	0.111111
Sector	0.600000	0.085714
Dominance(>250)	1.000000	0.151515
Dominance(top10%)	0.600000	0.142857

Figure 25: Necessary conditions binary data set + high success

Analysis of Necessary Conditions

Outcome variable: Highsuccessindicator

Conditions tested:

	Consistency	Coverage
LCDcategorisation250	0.150000	0.037975
LCD_categorisationtop10	0.500000	0.125000
CityHeadquarters	0.000000	0.000000
Country	0.700000	0.155556
UNGeoschemeSubregion	0.900000	0.136364
Sub-Industries	0.100000	0.058824
IndustryGroup	0.400000	0.105263
Sector	0.700000	0.107692

Figure 26: Necessary conditions categorial data set + high success

Analysis of Necessary Conditions

Outcome variable: Successindicator

Conditions tested:

	Consistency	Coverage
Country	0.521739	0.545455
UNGeoschemeSubregion	0.913043	0.583333
Sub-Industries	0.130435	0.428571
IndustryGroup	0.347826	0.444444
Sector	0.869565	0.571429
Dominance(>250)	0.956522	0.666667
Dominance(top10%)	0.565217	0.619048
CityHeadquarters	0.000000	0.000000

Figure 27: Necessary conditions binary data set + moderate success

```
Analysis of Necessary Conditions

Outcome variable: Successindicator

Conditions tested:
                           Consistency    Coverage
LCDcategorisation250       0.413043       0.481013
LCD_categorisationtop10    0.489130       0.562500
CityHeadquarters           0.043478       0.222222
Country                    0.554348       0.566667
UNGeoschemeSubregion       0.836957       0.583333
Sub-Industries             0.163043       0.441176
IndustryGroup              0.402174       0.486842
Sector                     0.804348       0.569231
```

Figure 28: Necessary conditions categorial data set + moderate success

11 Search Description and Selection Criteria

To identify and synthesize the most pertinent literature on standard-setting consortia, the methods used to identify and select relevant studies for inclusion in this literature review are described in this subsection. This literature review serves not only to ground our study in the existing body of knowledge but also to pinpoint the knowledge gaps that the research intends to address. The search was conducted using a combination of keywords and boolean operators in the Google Scholar database.

The keywords used for the search were "Technology/innovation-driven", "Consortia " and "Standardization". These keywords were selected to capture a broad range of studies on the topic while ensuring that the search results were relevant to the research question. Boolean operators were used to combine the keywords and to narrow down the search results. A search with the search query "Innovation-driven standardization" OR "Technology standardization" AND "consortia" OR "consortium" has been conducted, resulting in 1680 initial hits. To streamline the search output and focus on contemporary research themes, the inclusion criteria were limited to studies published from the year 2018 and onwards. This process yielded a total of 388 scholarly articles, each subjected to a preliminary review of its title and abstract. Among these, a subset of 18 articles was selected for their specific focus on the causal and contextual factors, or interaction strategies, that influence the phenomenon of innovation within consortia.

Subsequently, a detailed overview in Excel was compiled, which methodically categorizes each source according to its sector, thematic focus, potential influencing factors, identified knowledge gaps, and proposed avenues for future research. This comprehensive synthesis of the extant literature facilitated a clear understanding of the prevailing scholarly discourse and enabled the identification of research domains frequently suggested by various academics. Through this approach, the present gap in research was discovered and selected for further inquiry.