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A Configurational Approach to Maturity Model Development – Using fsQCA to Build a Multiple-Pathway Maturity Model

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Abstract:

Maturity models can be used as tools which depict the developmental trajectories of entity classes in domains and evaluate the relative position of an entity within this framework. However, their development process has been the focus of researchers and practitioners ever since, resulting in different procedures, development approaches, and conceptual models. Thus, a major criticism of maturity models is the often missing conceptual and theoretical grounding when it comes to the interpretation of the concept of maturity. To address this shortcoming, our research approach focuses on the rigorous development of a multiple-pathway maturity model. By following a sequential, theoretically grounded process, the resulting maturity model can be viewed as an instantiation of the predefined conceptual components and characteristics in a predefined domain. We present and discuss the instantiated sector and size-specific maturity model for innovation capability in small industrial firms, which is developed by applying configurational methods on a dataset and thereby offers multiple pathways to maturity. This concept of equifinality is central to our approach. It has rarely been considered in maturity model development research, although it offers the potential to build more realistic models with greater applicability, especially in domains with many interdependencies.

Keywords: Maturity Models, Configurational Set Theory, Innovation Capability, NCA, fsQCA, Equifinality.

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1 Introduction

Research in the field of information systems (IS) plays a major role when it comes to the evaluation or classification of emerging and complex phenomena and their impact on organizations (Pappas et al., 2018; Tilson et al., 2010; Vial, 2019). Maturity models (MMs) are tools that allow organizations in different domains to determine their current maturity within a pre-defined process or ability or offer guidance on how to improve this maturity along with their performance (Luftman, 2000; Tarhan et al., 2016). Due to their popularity in research and practice (Pereira & Serrano, 2020; Poeppelbuss et al., 2011; Proença & Borbinha, 2016), the number of articles published in the context of MM research has been rising constantly during the last years. Previous findings revealed that from 2002 to 2018, more than one third of the articles presenting MMs in journals and conferences were published between 2016 and 2018 (Pereira & Serrano, 2020).

The impact and importance of MMs for IS research is furthermore visible in a strong focus on the IT domain (i.e., Becker et al., 2009; De Bruin et al., 2005; Gollhardt et al., 2020; Luftman, 2000), whereas other MMs are distributed over various research areas (e.g., e-government (Singh et al., 2007), risk management (Doss et al., 2017), or health care (Thrasher et al., 2006). Likewise, in the field of business administration, Felch and Asdecker (2020) show that from 2001 to 2019, more than half of 130 business process MMs have been published within the last five years. However, they reveal that these publications are mainly published in scientific outlets with a low(er) recognition, creating a lack of opportunities for reviewers to reproduce the actual design of the developed MMs. Thereby, the reliability of research and the traceability of the underlying concepts is threatened, challenging the quality of the developed MMs along with their assumed relevance (Felch & Asdecker, 2020). This restriction also leads to a paradoxical situation where the applicability of MMs within organizations remains limited, regardless of their increasing presence in the literature as practice-oriented research goals (Felch et al., 2019; Tarhan et al., 2016). This might be due to their ad hoc development (Pereira & Serrano, 2020), leading to MMs with weak or no conceptual grounding with respect to their structural components and their composition. Another reason is the limited representation of how to improve—from the perspective of the assessed entity—what severely threatens MMs' validity in practice (Andersen et al., 2020). Many MMs are developed following deductive and literature-based approaches, mainly driven by developers identifying a need for a new MM for a specific field. Furthermore, domain-specific MMs are often provided for organizations of different sizes and sectors, assuming a one-size-fits-all representation of maturity which over-simplifies the concept of maturity in complex domains.

We propose that instead of developing new MMs using ad hoc approaches, the development process and the resulting MMs should be theoretically and conceptually grounded. Therefore, we encourage an empirical data-driven research approach to MM development, by applying configurational methods, such as fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 2008), while identifying necessary conditions in kind (Ragin, 2008) or both in kind and in degree with necessary condition analysis (NCA) (Dul, 2016). The theoretical grounding of the method along with other features such as equifinality provides an ideal methodological foundation for our approach. However, neither NCA, fsQCA, nor configurational methods in general are per se methods designed to build MMs. Applying them in this specific context with the objective of overcoming the mentioned MM challenges needs further elaboration. Thus, we propose the following research question (RQ):

> **RQ1: How can the development process of MMs be improved to better reflect domain complexity and to better represent the addressed target group by applying configurational methods?**

We contribute by exemplifying the creation of more realistic MMs through fsQCA, in response to recent requests for different development approaches and assumptions of maturity (Andersen et al., 2020; Felch & Asdecker, 2020). Adding to the ongoing discussion and the call for different development approaches and assumptions of maturity (Andersen et al., 2020; Felch & Asdecker, 2020; Lasrado et al., 2016; Solli-Sæther & Gottschalk, 2010), we argue that in complex domains with numerous interdependencies of organizational dimensions and processes, the assumption of a single path to maturity is an oversimplification that does not capture or depict reality in its variations. The applied concept of equifinality – stating that an outcome can be reached by different combinations of input variables – results in a multiple-pathway MM, providing different possibilities of maturation.

The instantiation of the proposed components in the domain of innovation capability (IC) demonstrates the applicability of MM development based on configurational methods, which results in an innovation capability maturity model (ICMM). It contains concepts specifically valid for the IC domain and its respective target group of small industrial companies (SICs). Thereby, we first answer the mentioned call for different development approaches and assumptions of maturity (Andersen et al., 2020; Felch & Asdecker, 2020; Lasrado et al., 2016; Solli-Sæther & Gottschalk, 2010) by providing a configurational theory and methods-based MM development process. Further, our MM instantiation contributes to the results of Mendoza-Silva (2021), who calls for ICMMs, which balance theory and practical applicability. Finally, we address the knowledge transfer problem raised, for instance, by Van de Ven & Johnson (2006), by providing a conceptual blueprint of the MM development process. Thereby, we offer a complementary approach on addressing practical problems (organizational maturity) by applying conceptually grounded theory and methods (configurational theory and fsQCA), which can be applied by researchers and practitioners likewise.

The remainder of this paper is structured as follows. First, the theoretical background covers MMs as well as configurational theory and methods. Section three presents the theoretical and conceptual components of an MM as well as its instantiation, an ICMM for SICs. Section four discusses the approach, its implications for research and practice, while section five concludes the paper by providing a summary of the results as well as pointing out the limitations and showing avenues for future research.

2 Theoretical Background

2.1 Maturity Model Development and Application

The main purpose of an MM is to demonstrate and assess an anticipated or desired path of improvement or development regarding a delimited subject area (capabilities or processes) for a defined target group (organizations, companies, departments) (Bley et al., 2020). As these models' intention can vary, their structure and the underlying interpretation of maturity can differ. They typically consist of: a) a number of levels (commonly 3-6), b) a generic description of each level, c) a number of dimensions, d) a number of factors, for each dimension, and e) a description of the performance of each activity or element as it might perform or might be performed at each maturity level (Fraser et al., 2002). The underlying maturity principle can be continuous or staged (Lahrmann & Marx, 2010). Continuous MMs allow for an assessment of single capabilities on different levels. These models offer the possibility of providing different maturity results within one domain depending on the individual maturity of the respective characteristics. Staged MMs, the most dominant form, provide a pre-defined constellation of capabilities or conditions which have to be met in order to reach a specific maturity level. Their basic assumption is that an organization is constantly evolving, inter- and intra-organizationally, due to learning effects and improvements (see Fig. 1).

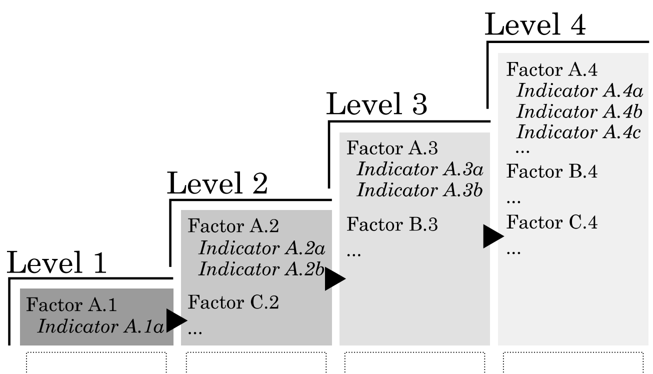


Figure 1. Structure of a Staged Maturity Model (Source: Bley et al., 2020)

Whereas continuous MMs provide a more flexible approach to maturity measurement (i.e., different dimension can be measured on different maturity levels), a staged structure combines an organization's maturity to a single maturity stage, offering a more lucid, however condensed result (Lahrmann & Marx, 2010; Sanchez-Puchol & Pastor-Collado, 2017). Not only the models' structure, but also the information content of the assessment result can vary. Descriptive MM focus on depicting and assessing a current situation of activities or capabilities of an organization, whereas prescriptive MM identify and propose potential improvement activities, thereby providing guidance for reaching a higher maturity level (Poeppelbuss & Roeglinger, 2011).

Although MMs are being constantly developed in research and practice, there exist several criticisms of current MMs and their development (Andersen et al., 2020). For instance, a common shortcoming is the lack of empirical validation when it comes to the selection of relevant factors and dimensions (Lahrmann et al., 2011), as well as theoretical grounding (Felch & Asdecker, 2022) leading, in the worst-case, to poorly designed models and, therefore, to difficulties and also risks in case they are used as benchmarking tools (Bannister, 2007). Another point of criticism is a simple copying of existing model structures from literature and therefore a missing conceptual and theoretical grounding (Coursey & Norris, 2008; Plattfaut et al., 2011), as well as the assumption of a single linear path rather than several different paths to maturity (Lasrado et al., 2015). Furthermore, many MMs – regardless of their maturity principle – differ in the use of maturity concepts, terminology, and semantics, making a comparison or general applicability challenging (Tarhan et al., 2016; Wendler, 2012). Therefore, the development of a conceptual overview might be useful as it provides a definition of such dependencies (Bley et al., 2020).

Another criticism is that MMs often take a one-size-fits-all approach to assessing the maturity in a domain, assuming that the same MM will be valid for very heterogeneous or even different target groups, i.e., in the case of companies, e.g., for companies of different sizes and sectors. This can be attributed to the fact that factor selection and combination are often derived conceptually from literature or expert knowledge (Pereira & Serrano, 2020) but are rarely data-driven based on a dataset of companies similar to the MM's target group. Therefore, more specific MMs addressing the needs of a smaller range of targeted organizations, such as by considering size (i.e., the maturity of a large company is not comparable to the one of a small company), industry, or any other relevant domain-driven segmentation, could improve an MM's usefulness and thereby its application in practice (especially within this more homogeneous target group).

Several guidelines exist addressing the development process of MMs (i.e., Becker et al., 2009; De Bruin et al., 2005; Mettler, 2010; Poeppelbuss & Roeglinger, 2011; Solli-Sæther & Gottschalk, 2010). However, they either focus on the development or discussion of MMs in specific domains like IT management (Becker et al., 2009) or business process management (Poeppelbuss et al., 2015; Poeppelbuss & Roeglinger, 2011), or their recommendations remain limited in their interpretability and validity as they do not provide terminology, common concepts or underlying structural components for the development process (Bley et al., 2020; Plattfaut et al., 2011). A more generalized, set-theoretic approach to MMs was first proposed by Lasrado et al. (2016). They presented a six-step-development approach, which is aligned to general MM development guidelines proposed by Becker et al. (2009), Mettler (2010), and Solli-Sæther and Gottschalk (2010), as well as to guidelines on methodological procedures for set-theoretic methods, like QCA (Fiss, 2011; Mattke et al., 2022; Pappas & Woodside, 2021; Schneider & Wagemann, 2012) and NCA (Dul, 2016). Whereas their approach focused on the general implementation of fsQCA in MM development without specifically mentioning domain complexity and target groups, we propose an MM development, which uses fsQCA and Necessary Condition Analysis (NCA) to specifically depict class specific requirements of the MM's target group, i.e., SICs, and also addresses domain complexity by supporting dimensions. Thus, we not only apply fsQCA and NCA as alternative development methods for MMs, but also highlight their ability to enhance an MM's potential as an instrument for guidance and improvement due to an empirically derived representation of the respective entity class.

For the domain we have chosen to demonstrate our approach, i.e., IC, several MMs or similar maturity assessment approaches addressing the domain of IC have been suggested in prior research. In one of the most recent ones, Zheng, Ulrich and Sendra-Garcí (2021) employ a configurational approach to investigate the antecedents of high innovation performance from a knowledge management and innovation ecosystem perspective. Corsi and Neau (2015) provided a 5-level MM for IC, which is based on the Capability Maturity Model Integration (CMMI) and offers the possibility to evaluate innovation potential per level and also provides descriptions of possible innovation improvement gains. Narcizo et al. (2018) conceptionally developed an IC assessment instrument, which was specifically designed for the evaluation of innovation performance resulting from small Brazilian low-tech companies' IC. It later served as a conceptual framework for a quantitative survey, which, however, included companies of all sizes (Eleutério Delesposte et al., 2019). Even though the authors were able to draw conclusions about the applicability of the instrument, the application of MMs for a target group other than the intended one is not recommended, due to the varying characteristics of the companies. Thus, we have chosen a domain which is quite complex and where there is an obvious interest in MMs, but in which no approach has yet established itself as dominant. Also, the need for target group specificity has already been raised.

To sum up, several shortcomings relate to the development and the application of MMs. First, the field is lacking empirical and theoretical grounding due to its dominant conceptual, literature-based and deductive approaches (Pereira & Serrano, 2020). Furthermore, due to the oversimplification of reality in existing MMs (Solli-Sæther & Gottschalk, 2010), the possibility of reaching maturity by more than one path is not allowed. This assumption is especially crucial in domains characterized by complexity, such as digital transformation and related innovation activities. Lastly, domain-specific MMs are often considered to be valid for companies regardless of their size or industry. However, given the differing individual characteristics of companies of different classes, this assumption is too simplistic – resulting in MMs which are rarely applicable.

2.2 Configurational Theory and Methods

In the context of explaining organizational complexity, configurational theory and methods have become increasingly important in recent years (e.g., El Sawy et al., 2010; Fiss et al., 2013; Park et al., 2020; Park & Mithas, 2020). Their main advantage lies in their aspiration to investigate the influence, interconnectedness, nonlinearity, as well as the discontinuity of conditions simultaneously, unlike variance approaches which try to reduce complexity by explaining the effect of single variables on the outcome (Meyer et al., 1993). The concept of equifinality allows detecting multiple configurations of conditions leading to the same outcome, representing a more realistic illustration of complex settings. Furthermore, causal asymmetry is representative of the assumed non-linearity of effects and describes situations where causes leading to the occurrence of the outcome can be different from the causes leading to its absence (Ragin, 2008). Set-theoretic methods can help bridge the gap between a theoretical conceptualization and a methodological approach towards configurational theory (Fiss, 2007; Fiss et al., 2013).

FsQCA can connect theoretical and configurational multiplicity (Park et al., 2020; Ragin, 2008; Ragin & Fiss, 2008). FsQCA, based on concepts of fuzzy set theory and formal logic, identifies single or combinations of conditions (configurations) that are sufficient or necessary for an outcome to occur (Ragin, 2008), instead of investigating main effects among variables and the outcome (Woodside, 2014). In fsQCA, each case can be assigned values from 0 to 1, which represent their membership in a set (i.e., how much they belong to a set or group), starting from being fully out of a set and ending with being fully in a set, respectively. This allows to identify multiple configurations of necessary and sufficient conditions, which are – through their presence or absence – responsible for the outcome to occur. A condition refers to the transformation of a variable (Mattke et al., 2021, 2022; Ragin, 2014). For instance, the variable "amount of internal innovation expenses" will be coded into the condition "high internal innovation expenses". Afterwards, the data will be analyzed for the configurations of present or absent conditions leading to the occurrence of the outcome.

This analysis is done by applying an algorithm which is based on Boolean and fuzzy logic as well as truth table minimization. A specialized software, which is based on this algorithm and therefore able to run such analysis, is 'fs/QCA'[1] (Ragin, 2018). The fs/QCA algorithm identifies two main types of conditions, these are core (strong causal relationship) and peripheral (weak relationship) conditions. Further, a "do not care" situation can occur, meaning that a condition's presence or absence is not decisive for the outcome (Fiss, 2011). The role of single conditions is not fixed, leading to different interdependencies between conditions in different configurations and thereby to stronger or weaker influences on the outcome (Park et al., 2020).

Besides the detection of sufficient conditions, fs/QCA can determine necessary conditions for an outcome to occur *in kind*, based on calibrated data. However, by employing NCA, we can detect necessity *in degree* by answering what specific level of a condition X_c is necessary for a particular level of the outcome Y_c (Vis & Dul, 2018). Thus, we complement fs/QCA with NCA to reveal the factor levels that are needed to reach a specific maturity level.

2.3 Conceptual Approach

This research approach offers a guideline for a rigorous development process of an MM, which is based on configurational theory and methods (Bley et al., 2021). The development process consists of a foundational part of concepts of the MM to be developed, which describes basic concepts of an MM, and which are valid for all kinds of MMs as they define and conceptualize an MM in its structure. Further, the concepts of the application of configurational methods, like NCA and fsQCA, for the MM development are

[1] http://www.socsci.uci.edu/~cragin/fsQCA/software.shtml.

presented and how they, when instantiated, result in configurational method-specific output for the depiction of maturity levels. The last part of the development process refers to the concepts needed, when the actual MM is applied, such as a tool to evaluate the organizations as well as potential maturation pathways (see Figure 2).

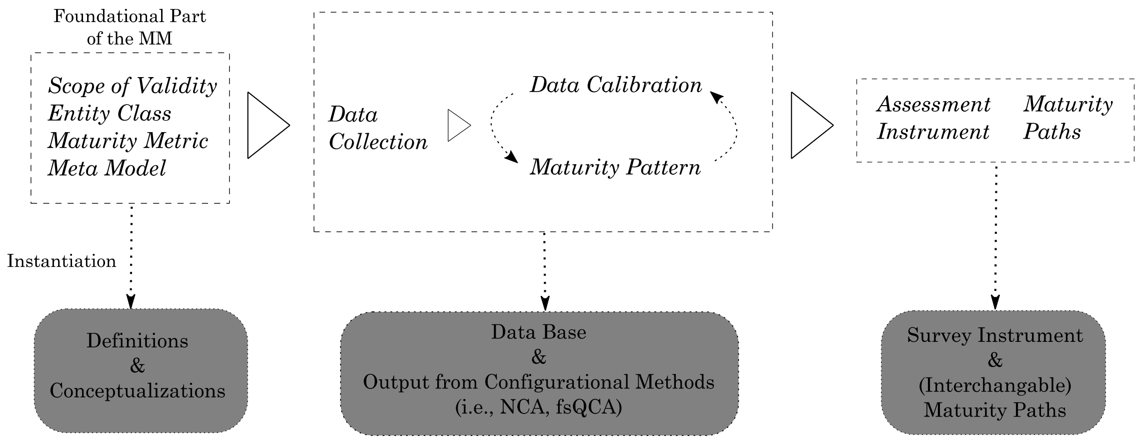


Figure 2. Conceptual Overview of Developing MMS Applying Configurational Methods

Whereas the foundational part of the MM development process refers to basic underlying characteristics of an MM and is rather descriptive (i.e., scope of validity of the MM, entity class of the MM, maturity metric and underlying relations in the Meta Model), the application of configurational methods will reveal specific results for a respective domain and target group, which influence the process of data collection, data calibration, and the resulting maturity pathways.

This research provides a guided approach on how to develop an MM applying configurational methods in complex domains. Since the current economic and organizational environment is characterized by complexity and a high level of interdependencies within processes and elements (Park et al., 2020), the ability of a company to continuously adapt to this multifaceted environment is vital for its competitiveness and can be characterized as its innovation capability (Zheng et al., 2021). Thereby, the domain of IC can be considered as a complex domain and within this paper it serves as an exemplary domain to illustrate our MM approach. We instantiate the concepts presented in Figure 2 in the domain of IC and use a dataset of SICs for the application of configurational methods. The results are qualitatively interpreted as well as tested for predictive validity and can therefore be regarded as an evaluation of the instantiated MM concepts. Table 1 provides an overview of the MM's concepts and the related tasks. The right column refers to the respective section in this paper.

Table 1. Description of the MM's Concepts and Activities.

Concept	Task Description	Instantiation Result	Exemplified in Section
Scope of validity	Defines the specific ecosystem or domain for which the intended MM is valid.	Definition	3.1
Entity Class	Represents all objects that can be empirically investigated in the design process of an MM. At the same time, it represents the target group of the MM.	Definition	3.2
Maturity Metric	Defines the theoretical conceptualization of maturity in the scope of validity by assigning maturity-relevant processes and activities (i.e., independent variables) to an outcome (i.e., a dependent variable).	Conceptualization	3.3
Meta Model	By aligning the MM development process to a meta model for MMs, different MMs can be regarded as instances of the meta model, leading to common semantics and syntaxes between the models, thus making the design process transparent and comprehensible.	Conceptualization	3.4
Data Collection	Process of planning and conducting the data collection.	Quantitative data base from questionnaire or	3.5

		other survey instrument	
Data Calibration	Transformation of the underlying raw data base to be able to apply configurational and set-theoretic methods. The calibration will influence the appearance of maturity patterns.	Necessary Condition Analysis (NCA): NCA Scatterplots and Bottleneck-Tables	3.6.1
		Fuzzy-set Qualitative Analysis (fsQCA): Calibrated data, based on qualitative arguments and descriptive statistics	3.6.2
Maturity Patterns	The application of configurational methods, based on the data calibration and in accordance with the maturity metric reveals the construct of maturity patterns.	Solution Tables with fsQCA configurations	3.7
Assessment Instrument	Development of an assessment instrument which can retrieve the same information used to develop the MM and which will be applied in organizations.	Questionnaire or other survey instrument (depending on the tool used for the data collection)	3.8
Maturity Paths	Interpretation of the fsQCA configurations for the organizations to be investigated.	Dimensional maturity paths and their interchangeability	3.9

In the following, each concept is first described theoretically ('concept') and then instantiated and described in the IC context ('instantiation').

3 Components of a Multiple-Pathway Maturity Model

3.1 Scope of Validity

Concept

Complex domains are characterized by diffuse interrelationships and interdependencies between factors that are responsible for the occurrence of an outcome, thus, they need to be narrowed down to a field of interest representing it. This scope of validity is not limited to any research domain and can be adapted to whichever scientific field of research. Following the configurational logic and its underlying approach to handling causal complexity, the researcher is free to choose the respective factors representing the desired research model if they can be measured qualitatively or quantitatively. Thus, the factor selection process can be based on theoretical knowledge following existing literature approaches or it can be more of a practical approach based on expert knowledge in a particular domain. Furthermore, the researcher is free to choose any combination or additional factors of their interest.

Instantiation

As scope of validity for our MM, we chose the domain of IC as a representative of a complex domain. It captures "the ability to continuously transform knowledge and ideas into new products, processes and systems for the benefit of the firm and its stakeholders" (Lawson & Samson, 2001, p. 384) and is a crucial competence when coping with these adaptations (Saunila, 2020). Thus, the IC of a company can be regarded as its ability to apply and implement the concept of innovation. Especially when it comes to the flexibility of organizations, for instance, to adapt to rapid and disruptive transformational processes, IC is crucial for economic competitiveness (Saunila, 2020). Relevant factors used for the operationalization of innovation capability of a company (i.e., organizational culture, external knowledge utilization, or employee creativity) can be found within different dimensions (i.e., knowledge or organizational) which are again highly interdependent and only in their interplay result in a high level of IC (Boly et al., 2014; Saunila, 2017; Saunila & Ukko, 2014). Several definitions and streams of IC can be found in the literature (Saunila, 2020), that mainly consider IC as the creation of *outcomes*, *processes*, and as a *potential* of an organization to produce innovations. *Outcomes* of IC can be distinguished as products (Çakar & Ertürk, 2010; Landoni et al., 2016; O'Cass & Sok, 2014), processes (Hervas-Oliver et al., 2016), or different organizational innovations (De Martino & Magnotti, 2018; Ilori et al., 2017). Considering IC as an ability of a company to perform the *process* of creating an innovative output represents the second stream of IC literature (Dadfar et al., 2013; Keskin, 2006; Lawson & Samson, 2001).

We draw on the third stream of research and examine IC as an innovation potential, in order to understand the existence of factors affecting the innovation potential of a company and therefore influencing its IC to produce innovations (Saunila & Ukko, 2012). Possible results of these activities can be product, service, or process innovations. This interconnected relation between innovation potential and capability represents the complexity of causal relations influencing the actual IC maturity of a company. However, this theoretical complexity will be considered in the application of configurational methods and the ability to make use of the concept of equifinality.

3.2 Entity Class

Concept

The decision on the investigated entity class in combination with the scope of validity will be decisive for the maturity metric. Similar to the freedom of factor choice for the scope of validity, the researcher is also free to choose the class of entities (i.e., companies of a specific size or sector) for which the MM will be valid. Thus, it is possible to develop an MM, which is based on representative data of the targeted class of entities and, thus, will be specifically valid for this (and only this) class of entities. Thereby, one of the major criticisms of MMs, which is that they often provide a one-size-fits-all approach for different or heterogenous classes of entities is addressed.

Instantiation

We chose the class of SICs in Germany as entity class for the MM to be developed. Although existing literature on IC provided evidence for a positive relation between IC and firm performance, particularly in small companies (Oura et al., 2016; Zhang & Hartley, 2018), the concepts of IC are not always apparent or feasible for this entity class (Saunila & Ukko, 2014). Constantly changing procedures of value creation within existing business models are challenging the industrial sector. Characteristic for the industrial structure is a large network of interdependent companies, in which especially small companies have a decisive position due to their specialized core competencies. Thus, they are often characterized by specialized activities, a lower degree of formalized communication, as well as flat hierarchies and structural flexibility. At the same time, they have to deal with financial constraints, inadequately qualified employees and missing cash-flow to generate products which can compensate weak turnover (W. Becker & Schmid, 2020; Bidan et al., 2012; Pullen et al., 2009; Tödtling & Kaufmann, 2002), making them dependent on a network of other firms and stakeholders.

3.3 Maturity Metric

Concept

After having chosen the scope of validity as well as the entities, the researcher now needs to decide about the relevant factors representing maturity in the chosen context and how they are influenced, dependent, and affected by each other. This accumulation of a dependent outcome, representing the scale for maturity, as well as independent factors, that influence the outcome, is characterized as maturity metric. At this point, the researcher combines the previous concepts of scope of validity and entity class and decides about maturity-relevant independent variables. As described above, they can be derived based on a literature review, via a practice-oriented ad-hoc approach, or by a combination of both.

Instantiation

In our research, the maturity metric development can be regarded as a hybrid approach to identifying IC maturity-relevant factors. First, we searched business and management literature for a state-of-the-art of IC factors in companies and aligned the identification of relevant concepts according to existing literature overviews in the field (i.e., Mendoza-Silva, 2021; Saunila, 2020) (Table 2).

Table 2. IC Concepts based on Mendoza-Silva (2021) and Saunila (2020)

Dimen-sion	Concepts	Authors(s)
Knowledge	Know-How development & management	(Branzei & Vertinsky, 2006; Calantone et al., 2002; Chang et al., 2017; Chen et al., 2010; Keskin, 2006; Koc & Ceylan, 2007; Liao et al., 2007; H. Lin, 2007; Perdomo-Ortiz et al., 2006; Podrug et al., 2017; Prajogo & Ahmed, 2006; Rahman et al., 2015; Sáenz et al., 2009, 2012; Saunila & Ukko, 2014; Tamer Cavusgil et al., 2003; J. Yang et al., 2006; Z. Yang et al., 2018; Yu et al., 2017)
	Skills & individual activity	(Çakar & Ertürk, 2010; Camps & Marques, 2014; Costa et al., 2014; Liao et al., 2007; H. Lin, 2007; Podrug et al., 2017; Romijn & Albaladejo, 2002; Rupietta & Backes-Gellner, 2019; Ryan et al., 2018; Wan et al., 2005; Winne & Sels, 2010; Yeşil et al., 2013)
	Cooperations & collaborations	(Akman & Yilmaz, 2008; Costa et al., 2014; Dunlap et al., 2016; Ganzaroli et al., 2016; Huhtala et al., 2014; Jones & Corral de Zubielqui, 2017; Jørgensen & Ulhøi, 2010; Kallio et al., 2012; Keskin, 2006, 2006; M.-K. Kim et al., 2018; Kyrgidou & Spyropoulou, 2013; Lai et al., 2015; R. Lin et al., 2010; Lisboa et al., 2011; S. Liu, 2009; X. Liu et al., 2013, 2017; McKelvey & Ljungberg, 2017; Ngo & O'Cass, 2013; O'Cass & Sok, 2014; Panayides, 2006; Perdomo-Ortiz et al., 2006; Quintana-García & Benavides-Velasco, 2016; Rahman et al., 2015; Rhee et al., 2010; Saenz & Pérez-Bouvier, 2014; Taherparvar et al., 2014; Weber & Heidenreich, 2016, 2018; Y. Zheng et al., 2010)
Organization	Resources and organizational structure	(Akman & Yilmaz, 2008; Çakar & Ertürk, 2010; Chang et al., 2017; Chen et al., 2010; Costa et al., 2014; Dadfar et al., 2013; Delgado‐Verde et al., 2011; Kallio et al., 2012; Koc & Ceylan, 2007; Lawson & Samson, 2001; Lemon & Sahota, 2004; S. Liu, 2009; Naranjo Valencia et al., 2010; Prajogo & Ahmed, 2006; Rahman et al., 2015; Sher & Yang, 2005; Wan et al., 2005; Z. Wang et al., 2016; C.-C. Yang et al., 2009; Z. Yang et al., 2018; Yeşil et al., 2013; L. Zheng et al., 2021)
Management	Management and Leadership	(Akman & Yilmaz, 2008; Costa et al., 2014; Delgado‐Verde et al., 2011; M.-K. Kim et al., 2018; Koc & Ceylan, 2007; Kyrgidou & Spyropoulou, 2013; Lai et al., 2015; H. Lin, 2007; S. Liu, 2009; Perdomo-Ortiz et al., 2006; Podrug et al., 2017; Prajogo & Ahmed, 2006; Quintana-García & Benavides-Velasco, 2016; Rahman et al., 2015; Rhee et al., 2010; X. Wang & Dass, 2017; Yeşil et al., 2013)

In a first step, we summarized the concepts into three dimensions of IC concepts: knowledge, organization, and management (left column, Table 2).

The *knowledge dimension* comprises innovation activities aiming to store, expand and efficiently use know-how resources inside and outside the company (L. Zheng et al., 2021). Previous research highlights the crucial role of handling existing and potential knowledge by companies to create innovative output (Saunila & Ukko, 2014; Tura et al., 2008). For instance, internal sources like prior work experience or education (Rupietta & Backes-Gellner, 2019), as well as external sources like suppliers or customers are found to facilitate IC (Romijn & Albaladejo, 2002), external networks (Jørgensen & Ulhøi, 2010; M.-K. Kim et al., 2018; X. Liu et al., 2013) and organizational learning activities (Smith et al., 2008). These skills are needed for building and maintaining IC throughout the company and include, for instance, continuous learning orientation (Calantone et al., 2002), staff development through education or experience, as well as the collaboration with external firms for external input not available within the company and for innovation success (Ganzaroli et al., 2016).

The *organizational dimension* combines activities and concepts, aiming to align the company's structure in an innovation-oriented manner and adapt to a changing business environment (L. Zheng et al., 2021). It focuses on the handling of organizational resources (Smith et al., 2008), the structure and expenses for research and development (R&D) activities (J. Kim & Choi, 2020), the generation of innovative processes and their implementation (Lawson & Samson, 2001), as well as the way the company deals with innovation creating activities (Saunila, 2016). Such activities focus on building an internal system of requirements to create and maintain structures for IC.

Another research stream emphasizes IC's *management dimension* with activities related to management commitment and leadership behavior. It combines factors like a company's vision and strategy (Smith et al., 2008) with an innovation supportive leadership culture (Saunila, 2016), which enables and encourages employees to take risks to create innovative ideas without fearing failure (Wan et al., 2005). However, due to their internal structure, small companies often lack dedicated management staff, which is why here we focus on the knowledge and organizational dimension.

After having identified the broader IC dimensions, we further narrowed down the range of possible maturity factors in the entire scope of IC validity to the factors that match our dimensions' definitions, are mentioned in an SME, and/or industrial context. For the data collection, we make use of the German data base "Mannheim Innovation Panel" (MIP), which is an annual panel survey that fully complies with the *Oslo Manual* which provides guidelines for collecting, reporting, and using data on innovation activities (OECD & Eurostat, 2005, 2019). Therefore, we matched the identified IC results from literature with factors in the questionnaire provided by the MIP (Table 3).

Table 3. Overview of IC Factors

	Factor (according to the MIP Questionnaire)	**Definition**	**References**
Knowledge Dimension	Internal innovation expenditure Educated employees External know-how Cooperation	Activities/concepts aimed at storing, expanding and efficiently using know-how resources inside and outside the company	(Dunlap et al., 2016; Ganzaroli et al., 2016; Kallio et al., 2012; X. Liu et al., 2013; O'Cass & Sok, 2014; Romijn & Albaladejo, 2002; Rupietta & Backes-Gellner, 2019; Saunila, 2020; Smith et al., 2008; Weber & Heidenreich, 2016, 2018; Winne & Sels, 2010)
Organizational Dimension	Work organization R&D activities Intensity of R&D activities Development of innovation expenditure Flexibility/Adaptability of business processes Third-party R&D	Activities/concepts aimed at aligning the structure of the company in an innovation-oriented manner	(Dadfar et al., 2013; Kallio et al., 2012; Lawson & Samson, 2001; OECD & Eurostat, 2005, 2019; Sher & Yang, 2005; L. Zheng et al., 2021)
Outcome	Turnover generated by innovative products		(O'Cass & Sok, 2014; Oura et al., 2016; Saunila, 2017; Zhang & Hartley, 2018)

Since we subsequently work with a dataset developed following the IC guidelines proposed by the Oslo Manual, we have combined our theoretical findings on IC in SMEs with those. Table 3 provides an overview of the selected factors as well as the dependent variable, which will be used as the outcome (i.e., for the measurement of IC maturity). We derived four factors in the knowledge dimension and six factors in the organizational dimension. Following the configurational and fuzzy logic, these factors will subsequently represent the various maturity levels in different values and configurations.

3.4 Meta Model

Concept

In order to develop a conceptually grounded MM, its concepts must match a semantically as well as syntactically rigorous framework. An exemplary UML-based approach – a meta model for MMs – can be found in Bley et al. (2020), who present a conceptual overview of MM components, their relationships and dependencies. The conceptualization of a meta model is developed subsequently to the definition of the scope of validity, the entity class, and the maturity metric as these concepts and their relations need to be known to the researcher in order to derive the framework.

The concepts of an MM according to the respective relations are defined in Table 4, which provides a conceptual overview of the MM and, therefore, allows other researchers as well as MM users to comprehend and understand the model's components and structure.

Not all MM concepts need to be instantiated in this particular step of the method application as they only become relevant when the respective MM will be applied. For instance, the concepts of *Indicator* and *Indicator Type* refer to the measurement of a specific factor within a company and need to be defined when the valid MM is going to be applied in the company. However, since an empirical development approach is applied for the MM, it is recommended to use the same indicator type for the application of the MM and for the collection of data for MM development.

Table 4. Maturity Model Concepts and Definitions (Bley et al., 2020)

Concept	Definition
Maturity Model	Model for the assessment of the relative fulfillment or ability (maturity) of an organizational entity in a *domain*; can be specified by *dimensions* and consists of several *maturity levels*
Domain	Field of interest for which the *maturity model* is developed
Dimension	Subdivision of an organizational entity's structure into areas of interest and results from the context of a *maturity model* applied; can aggregate *factors* related to it
Factor	Property of the organizational entity, which represents the object/area/process of investigation; used by one or more *maturity level* and can be related to a *dimension* within an organizational entity
Factor Specification	Technical and foundational requirement construct for determining the *maturity level;* acts as the *maturity level*'s individual expression of a *factor* (needed due to multi-usage of factors)
Indicator	Measurable property of one or more *factors* within an organizational entity; uses an *indicator type* for measurement
Indicator Type	Measuring method for determining the *indicator's* value
Maturity Level	Rank of the organizational entity's maturity that results from factor evaluation by using the *factor specification* or aggregation of a dimension's related factors; subdivides the *maturity model* and represents a relative degree of an organizational entity's ability/maturity

Instantiation

The previously derived scope of validity, dimension, and factors representing IC in small companies are explained and their dependencies and relationships are further described (see Table 5). In the development process of the ICMM the classification of the meta model's concepts and the step of data collection is intricately linked to each other, as the concept of factor specification, indicator, and indicator type are dependent on the data collection method and the underlying evaluation criteria. In our approach, the *indicator* refers to the specific question in the questionnaire which is measured by the *indicator type* (nominal or ordinal scales, as well as scale 1 or 2 (Table 5).

Table 5. Definition of IC Meta Model Concepts

	Factor Specification	Indicator	Indicator Type
Knowledge Dimension	Proportion of internal innovation expenditure *(Int. InnoEx)*	Innovation expenditures for supporting internal activities (e.g., training and market preparation, development, implementation activities for innovations)	Scale 1
	Proportion of employees with higher education *(Edu)*	Share of employees with a higher education certificate or degree.	Scale 2
	Proportional expenditure for the acquisition of external know - how *(Ext. Know-How)*	Acquisition of external knowledge like patents, scientific, technical services for product and process innovation.	Scale 1
	Innovation - related coope-ration with other firms or public research institutions *(Coop)*	Participation in joint innovation projects with other enterprises.	Nominal (yes/no)
Organizational Dimension	New forms of work organization *(New Work)*	Introduction/innovation of new methods of work organization.	Nominal (yes/no)
	Proportion of R&D carried out by the firm itself *(Own R&D)*	Share of experimental R&D activities conducted by the company itself.	Scale 1
	Continuous R&D activities *(Cont. R&D)*	Continuous internal R&D.	Ordinal (no; occasional; continuous)
	Development of innovation expenditure in the current year *(Dev. of InnoEx)*	Development of innovation expenditure in the year 2017.	Ordinal (not known yet; decreasing; steady; increasing)
	New methods for the organi-zation of business processes *(New BP)*	Introduction of new methods business processes.	Nominal (yes/no)

	Share of R&D by third parties *(Third party R&D)*	R&D activities purchased from public or private research organizations or companies.	Scale 1
Outcome	Proportion of total turnover from innovative products.	Proportion of total turnover generated from new or clearly improved products.	Scale 2

Note:	Value	0	1	2	3	4	5	6	7	8	9	10
Scale 1	Range in %	0	<10	<20	<30	<40	<50	<60	<70	<80	<90	≤100
Scale 2	Range in %	0	<5	<10	<15	<20	<30	<50	<75	≤100		

3.5 Data Collection

Concept

In accordance with the maturity metric, the researcher needs to collect data from the class of entities for which the MM is intended to be valid. This is done by a respective tool (questionnaire, interviews), which suits the research question and research approach best. Another option is to use existing data bases, i.e., data collected by other researchers. Since the MM will be developed based on an empirical data base, the requirement is a sufficiently high number of cases in relation to the number of conditions (Schneider & Wagemann, 2010). There does not exist a general case-condition-ratio, but a common rule of thumb is to have approximately 2^k observations, with k as the number of conditions.

Instantiation

The ICMM was developed using data from SICs focusing on the factors and indicators previously derived by literature and theoretical implications. As mentioned above, we made use of the MIP, which is developed by the Centre for European Economic Research (ZEW), commissioned by the Federal Ministry of Education and Research (BMBF), and since the first survey in 1993 it is updated on a regular basis, depending on the latest recommendations of the Oslo Manual.

The MIP supports the analysis of different Innovation indicators like persistence in innovation activities, the causal effects between innovation input and output, as well as between innovation and firm performance. Every two years, the MIP is part of the "Community Innovation Survey" (CIS), meaning German companies of different sizes and sectors answer a broader question pool and thus provide a larger data base of IC related factors. Due to its flexibility with regard to new questions (e.g., through the annual survey rhythm), the MIP offers an opportunity to take up and examine current topics of innovation and technology policy based on recent scientific findings to measure innovation (Peters & Rammer, 2013). For the development of the ICMM the dataset of 2017 was used. As it was included in the CIS, it provided the relevant information of the relevant factors and indicators, representing the foundation for further analysis and the empirical groundwork for the application of configurational methods.

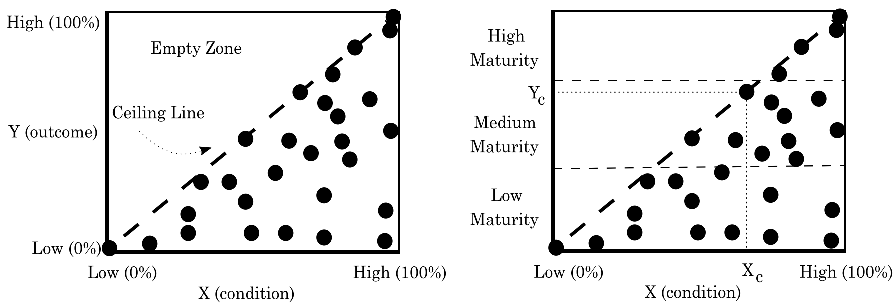
Transferring the recommended number of observations to our maturity metric, which consists of two dimensions with four and six conditions, the dataset should provide at least 2^4 (=32) and 2^6 (= 64) observations. The initial dataset contained information on 5.180 companies from different sectors and sizes and 272 IC variables. After reducing the set to small companies in the industrial sector with full detail of all IC-relevant factors we have identified in the maturity metric for the MM, we derived a dataset of 224 companies, of which 49% belong to the classification of ‘research-intensive-industry’ (e.g., chemicals, machinery, automobile) and 51% to ‘other industry’ (e.g., food, textiles, maintenance).

3.6 Data Calibration

3.6.1 Necessary Condition Analysis (NCA)

NCA is an approach to identify the “critical (levels of) determinants that are necessary for achieving the outcome and that must be put and kept in place in order to make it possible to achieve the desired outcome” (Dul, 2016, p. 41). By plotting the value of the potential necessary condition (X) of each case against the outcome (Y), the size of the empty zone in the upper left corner of the diagram reveals whether a condition is necessary for the outcome (Dul, 2016). Figure 3 shows an example of an idealized scatterplot of a necessary condition with a completely empty upper left corner on the left-hand side and the ceiling line as separation of the area with observed data. The size of the empty zone—and thereby the importance of the condition as a necessary condition for the outcome—is measured in the effect size *d.*

Similar to the correlation coefficients *r* or R^2, the effect size of a necessary condition ranges between $0 \leq d \leq 1$, with a larger *d* indicating a stronger necessity for the outcome. While scatterplots provide a visual representation of a condition's necessity, a bottleneck-table displays the certain degrees of the condition and the outcome (Figure 3 right-hand side) (Dul, 2016).



Outcome	Int. Innov Ex	Edu
0	NN	NN
10	NN	NN
20	NN	NN
30	NN	NN
40	NN	NN
50	NN	NN
60	NN	NN
70	NN	NN
80	NN	NN
90	10	37.5
100	10	37.5
Effect Size	0.012	0.047
	small	small
Ceiling Line	CE-FDH	CE-FDH

Figure 3. Scatterplot of a Necessary Condition (Dul, 2016), Conceptual Scatterplot of an MM Approach, Bottleneck-table with Necessary Conditions at the 90% Level

Concept

The transformation of the underlying data is a crucial step as it will be decisive for the resulting maturity patterns. Since there exist different types of configurational methods (fsQCA, csQCA, mvQCA[2]), the data requires different modifications in order to be applied for analysis. Especially the application of fsQCA on the dataset requires a thoroughly reasoned modification of each independent factor and the outcome separately. However, prior to the process of calibration, the data is tested for necessary conditions by applying the method Necessary Condition Analysis (Dul, 2016).

Instantiation

For the MM for SICs in the domain of IC we first tested if any of the 10 conditions are necessary to reach maturity. By identifying the necessity of an individual condition for the outcome (bivariate NCA) or the necessity of a set of necessary AND-configurations (multivariate NCA) (Vis & Dul, 2018), possible boundary conditions can be revealed that have to be present in order to reach a specific outcome (Lasrado et al., 2016). To be able to display a possible necessity of each factor against the outcome, we used the NCA R-package (Dul, 2020), which allows for the derivation of scatterplots and bottleneck-tables in a graphical demonstration[3]. We apply NCA to investigate the non-modified, raw data, which is why the data is directly loaded into the working directory and the analyses are run on each single factor as well as on the combinations of factors of the respective knowledge and organizational dimension. Running the analysis reveals three features, which can be directly interpreted. First, the effect size *d (0,1)* reveals how strong the effect of necessity is on the outcome variable; with $d < 0.1$ as small effect, $0.1 \leq d < 0.3$ as medium effect, $0.3 \leq d < 0.5$ as large effect, above 0.5 as very large effect (Dul, 2019) (see Figure 4 top). Besides its numeric value, *d* is displayed as the size of the area without observation when the variable is plotted against the outcome (see Figure 4 bottom).

[2] An overview and explanation of the methods crisp set QCA and multi-value QCA can be found in Ragin (2008) and Schneider and Wagemann (2012).
[3] An introduction into using the NCA R-package can be found here: https://repub.eur.nl/pub/78323/.

```
-----------------------
Effect size(s)
       ce_fdh      cr_fdh
edu    0.047       0.023
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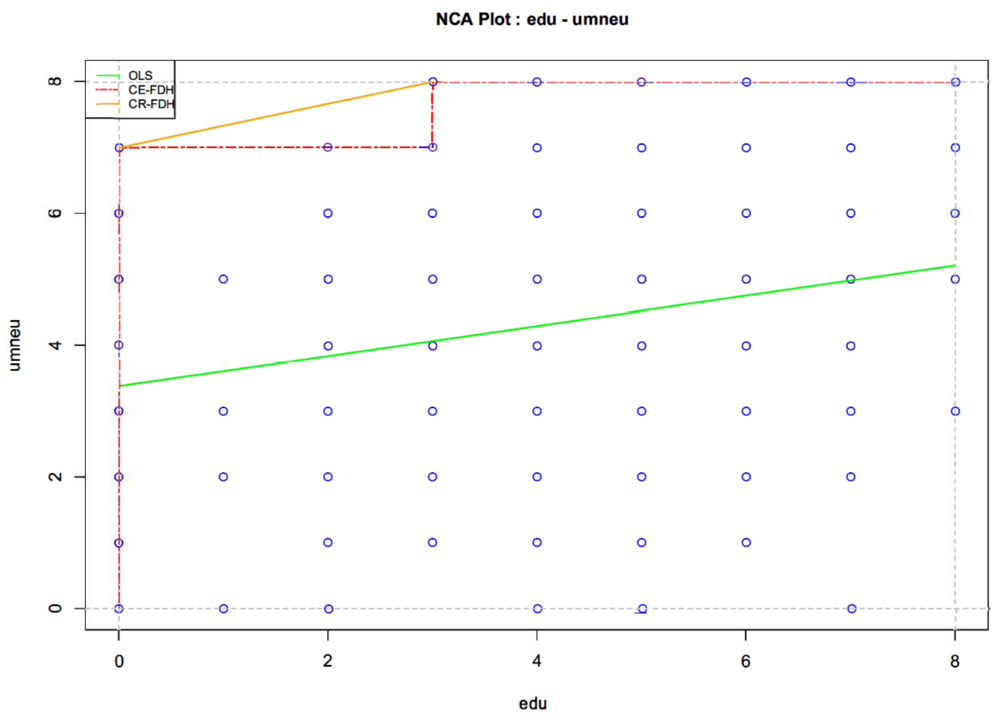

Figure 4. NCA Output of the Effect Size D (top) and the Scatterplot for the Factor "edu" (Bottom)

The abbreviations ce_fdh and cr_fdh refer to ceiling lines, which separate the areas with and without observations. A graphical depiction of those lines can be found in a scatterplot – which is the second feature of an NCA analysis (Figure 4, bottom and Figure 5). It plots the observations of a variable (blue dots) on the x-axis against the outcome on the y-axis. Ceiling envelopment with free disposal hull (ce_fdh) is a partially linear ceiling line (red line in Figure 4 and Figure 5), which delimits the range of observation of the expressions mainly of dichotomous and discrete variables. It displays, which level of X is necessary for reaching a respective level of Y. In Figure 4 (bottom), it can be interpreted as "A value of 3 of the factor "edu" is necessary for reaching the value of 7 of the outcome". Ceiling regression with free disposal hull (cr_fdh) is used for mainly continuous variables (yellow line in Figure 4 and Figure 5). It smooths parts of the ce_fdh-ceiling line and, therefore, reduces the ceiling zone's size but can thereby be used for further analysis (Dul, 2019).

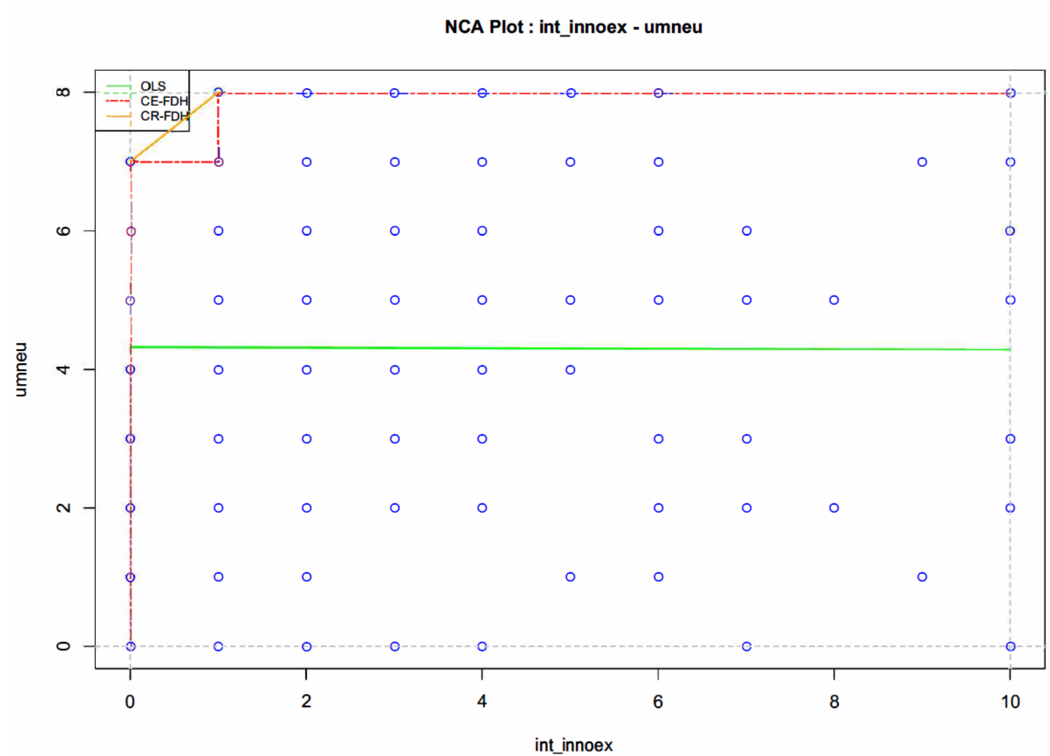

Figure 5. NCA Scatterplot of the Factor “Proportion of Internal Innovation Expenditure” (int_innoex)

Besides the graphical demonstration of observations and ceiling lines, NCA offers the possibility to present the results in a bottleneck table, which is the third feature offered by the R-package. It illustrates the minimum amount of the variable X that is required for a respective level of the outcome Y in a percentage range.

Bottleneck CE-FDH (cutoff = 0)
Y umneu (percentage.range)
1 edu (percentage.range)

Y	1
0	NN
10	NN
20	NN
30	NN
40	NN
50	NN
60	NN
70	NN
80	NN
90	37.5
100	37.5

Bottleneck CE-FDH (cutoff = 0)
Y umneu (percentage.range)
1 int_innoex (percentage.range)

Y	1
0	NN
10	NN
20	NN
30	NN
40	NN
50	NN
60	NN
70	NN
80	NN
90	10.0
100	10.0

Figure 6. NCA Bottleneck Tables of Factors “edu” and “int_innoex”

This feature is directly transferrable to the concept of MMs. The outcome variable can be understood as a maturity scale, and a possible necessity of a condition can be interpreted as a bottleneck for reaching a specific level of maturity. In Figure 6 (left-hand side), the respective bottleneck condition would be formulated as *“to realize 90% of the outcome, there need to be at least 37.5% of variable edu”*. Likewise, in Figure 6 (right-hand side), the respective bottleneck condition would be formulated as *“to realize 90% of* *the outcome, there need to be at least 10% of variable int_innoEx"*. Furthermore, a possible necessity on different levels can guide the researcher in selecting the borders for the maturity scale. In our analyses, there exists a weak necessity for variable edu (d=0.047) and int_innoEx (d=0.012) on the 90%-level. As our analysis revealed the same 90%-level for two different factors, we assumed there is a subtle difference for the companies in passing this level. Thus, we concluded that reaching 90% of the outcome could be considered as the border for "high maturity". However, the small effect size shows that the proportion of each factor for the occurrence of this outcome is low. Thus, we proceed to test for sufficient conditions by employing fs/QCA. Furthermore, since both factors revealed their necessity for the same outcome level, we used this value to draw the first boundary condition for the level of high maturity at 90% of the outcome variable, which was translated to the given value of 7 on the outcome scale 2 (Table 5). Since no other factors showed a necessity on a lower outcome level, we chose the boundary condition for low and medium maturity based on theoretical and empirical knowledge.

3.6.2 Fuzzy-set Qualitative Comparative Analysis (fsQCA)

The application of fsQCA requires a modification, called calibration, of the chosen variables and the underlying raw dataset (Ragin, 2008)[4]. By transforming the underlying factor values into fuzzy sets ranging from 0 and 1, the software "fs/QCA"[5] will afterwards be able to determine the configurations of conditions leading to the presence of the outcome of interest. This transformation, part of the direct calibration, is done by selecting three thresholds (or anchors) that define the full set-membership, the full-set non-membership, and a crossover point of maximum ambiguity between these two thresholds (Ragin, 2008). Then, each case is assigned a new value according to its own set-membership, a process done automatically by the software fs/QCA after selecting the respective anchors. For the calibration, the underlying theory and the researcher's experience and knowledge should always be considered to avoid ad-hoc calibration (Ragin, 2008; Wagemann et al., 2016).

Calibration

Especially the decision about the 0 and 1 anchors, which represents a case as being fully out or fully in a set as well as the assignment of the 0.5 crossover point, representing a case being neither in nor out of a set, is the most critical step. Due to an ongoing discussion of configurational methods in research, different streams of guidelines evolved over time (Mattke et al., 2022; Pappas & Woodside, 2021; Schneider & Wagemann, 2010; Thomann & Maggetti, 2020; Verkuilen, 2005). From a visual perspective, the fuzzification of data will draw a curve between the two extreme points 0 and 1; from a mathematical perspective, this step requires a membership function, which generates the curve. This curve can have different shapes, such as linear, quadratic, root, s-function, Bell-curve, or logistic (Kvist, 2006; Thiem, 2014). On this curve the data points are distributed according to the fuzzy set membership function, which represents 'the fundamental quantity necessary to use fuzzy sets' (Verkuilen, 2005, p. 464f.). Given the importance of the decision on the fuzzy set anchors in combination with the variety of existing membership functions and the resulting solution space, the process of calibration becomes a multidimensional and complex process, that the researcher has to face prior to data analysis. Especially the decision about the 0.5 crossover point has, depending on the underlying membership function and the dataset, major influence on the form and position of the curve in the solution space. Given existing literature and research in this area, researchers argue for a primarily theoretical argumentation when deciding about set membership scores, resulting in a rather qualitative approach to the data (Ragin, 2008; Schneider & Wagemann, 2010; Wagemann et al., 2016), with recent papers offering a good amount of details on how to calibrate interview data and employ fsQCA (e.g., Iannaci & Cornford, 2018; Tasoulis et al., 2023). Another large stream of researchers supports a data-based transformation, taking internal characteristics and statistical measurements into account, thus focusing on a more quantitative approach (Mattke et al., 2022; Pappas & Woodside, 2021; Thiem, 2014)[6]. There does not exist a unified opinion about the correct approach to calibration in research yet. Whereas Schneider & Wagemann (2010) state that a "mechanical application of mathematical operations is almost always wrong" (p.7), Thiem (2014) argues that "the use of data-based transformations is sometimes more appropriate, particularly when theory-based criteria are difficult to establish" (p. 640). From this methodological complexity, the resulting breadth of discussion of the results can already be deduced. Hence, researchers propose different

[4] A detailed description on how to apply fsQCA in IS can be found in Pappas and Woodside (2021).
[5] More information on the application of the software "fs/QCA" can be found in Ragin (2018).
[6] Further discussion about different approaches QCA and "their emphasis on cases, their conception of a valid explanation, and their mode of reasoning" (p. 379) can be found in Thomann & Maggetti (2020).

approaches for dealing with fsQCA's methodological challenges. A common suggestion is to avoid the direct assignment of the 0.5 crossover threshold as membership scores to cases, as those cases cannot be assigned to truth table rows according to the software's algorithm and thus will be dropped from the analysis (Wagemann et al., 2016). As a solution to this adding a constant of 0.001 to every set value below 1 is suggested (Fiss, 2011). However, this approach 'is arbitrary and should not become common practice' (Wagemann et al., 2016, p. 5). Later on, Fiss' (2011) approach was extended by additionally subtracting a constant of 0.001 of every set value and comparing the results for robustness (Maier et al., 2021). But for a case being above (+0.001) or below (-0.001) the fuzzy set anchor of 0.5 means being considered in or out of a set. Thus, even a small adjustment of adding or subtracting 0.001 can have a (major) impact on the results[7]. In fact, when running sensitivity tests on different membership functions and the resulting coverage, Thiem (2014) was able to show a high sensitivity of linear, quadratic, root, and logistic functions as well as the coverage measures towards small changes in the calibration set up. Therefore, and since there are no established robustness tests for fs/QCA solutions yet, we adopt Wagemann et al.'s (2016) recommendation and refrain from the technique of adding or subtracting a constant to our fuzzy values and follow a data-driven calibration approach, even if it includes the not preferred but accepted spare use of 0.5 membership scores (Ragin, 2008).

Even though the application of R for (fs)QCA analyses is becoming more popular recently, the fs/QCA software is used by most researchers for running QCA analyses. It is based on a logistic function, which never reaches values of 0 and 1. This limitation is often considered in the calibration process by assigning the values of the 0.05 and 0.95 percentile as 0 and 1 anchors to the dataset (Pappas & Woodside, 2021; Ragin, 2008). Furthermore, by taking data skewness and specific case characteristics based on descriptive statistics into account, the problem of limited diversity and subset relationships can be reduced (Cooper & Glaesser, 2016a; Schneider & Wagemann, 2012; Thomann & Maggetti, 2020). As our data base consists of 224 cases, thus a medium sized sample, we follow a data-driven calibration approach and examine deviation, frequency, and skewness of the data. In the initial data collection, the same questionnaire is utilized for data collection for small, medium, and large companies in different sectors, thus the respective item scales apply uniformly across all companies. However, due to the companies' individual characteristics, the values are not always comparable and should be qualitatively interpreted. FsQCA allows us to take into account companies' individual characteristics when performing the analysis.

Outcome Calibration

For the development of the MM the most crucial step is the calibration of the outcome as it represents the dependent variable and is therefore directional for the characterization of the resulting maturity paths. For instance, the researcher needs to decide on the number of maturity levels and thereby on the number of software runs. The result of these outputs is a pool of solution terms for each maturity level representing the concept of equifinality that enables a company to choose its own, that is, the best fitting maturity path.

The indicator for the measurement of the outcome is a proportion of the turnover by clearly improved or new products and is seen as a proxy for the IC of a company. The empirical assessment was done by applying scale 2 as indicator type (see Table 4). By calibrating the outcome variable, the respective raw data values are transformed into fuzzy set values (Pappas & Woodside, 2021; Ragin, 2008). We examine low, medium, and high maturity; thus, we calibrate the outcome three times based on different thresholds (Table 6).

The NCA revealed two necessary conditions for reaching 90% of the outcome variable, so we set the full-set membership anchor for high maturity on scale 2 at 7 (i.e., 87.5%) and the crossover point at 6, that equals a proportion of turnover of less than 50%, since the absolute distances on the scale were not evenly distributed. For the medium maturity level, we chose 6 as full-set membership and used the mean value (4.31) for the crossover point, indicating that all companies with a proportion of turnover of less than 20% (given value of 4 on scale 2) are considered more out than in the set of medium maturity but with a value of more than 20% but less than 30% (given value of 5) more in than out of the set. Finally, for the low maturity level, we chose the mean value of 4.31 as full-set membership with a crossover point at 3 (less than 15% proportion of turnover). For all levels, we set the anchor for full non-membership at 0.

Factor Calibration

[7] Cooper & Glaesser (2016b) provide an exemplary overview of how sensitive QCA solutions are for changing the threshold and/or the crossover point by small amounts.

When deciding on the calibration of the underlying factor values it is important for the researcher to take the respective case and data knowledge into account. For example, a consideration in our research context is, that it is more likely for a large company to be able to invest higher amounts into internal innovation-related expenses than it is for a small company due to its limited financial scope (Bidan et al., 2012). Consequently, the threshold for a small company to be fully in the set of high internal expenses for innovation-related expenditure is set at a lower position than it would be for a large company. For example, on scale 1 (see Table 6) the threshold for full set-membership in “high internal innovation expenditure” is set at 7 for a small company, implying that a small company, which spends more than 60% but less than 70% of its innovation expenses on internal innovation-related topics, is considered being fully in the set. Accordingly, we considered the statistical measures of the underlying dataset as it provides a general overview of the small companies’ distribution. We were thereby able to capture skewed results for the decision on qualitative calibration anchors.

Table 6. Descriptive Statistics and Fuzzy-set Anchors for Data Calibration

	Variable/Condition	Mean	SD	Minimum	Maximum	Fuzzy-set anchors
Outcome	Proportion of turn-over by new or clearly improved products	4.31	2.21	0	8	Low Maturity: 4.31 – 3 – 0 Medium Maturity: 6 – 4.31 – 0 High Maturity: 7 – 6 – 0
Knowledge	Int. InnoEx	2.49	2.81	0	10	7 – 2.49 – 1
	Edu	4.06	2.43	0	8	7 – 4.06 – 1
	Ext. Know-How	0.35	1.15	0	10	2 – 1 – 0
	Coop	0.34	0.48	0	1	1 – 0
Organizational Dimension	New Work	0.29	0.46	0	1	1 – 0
	Own R&D	4.53	3.61	0	10	9 – 4.53 – 1
	Cont. R&D	1.24	0.88	0	2	2 – 1 – 0
	Dev. of InnoEx	2.93	0.93	1	4	4 – 3 – 2
	New BP	0.35	0.48	0	1	1 – 0
	Third party R&D	0.59	1.35	0	8	4 – 2 – 0

For the calibration of the original data, we ran a descriptive analysis, analyzed the distribution of the data and chose the value of the 90th percentile as full-set membership anchor and the given value of 1 as full-set non-membership for the factors Int. InnoEx, Edu, and Own R&D. For Cont R&D and Dev. Of InnoEx we chose the highest and lowest ordinal value as full-set and non-set membership, respectively. For the nominal data, we chose the answers “yes” as being fully in the set (fuzzy set value 1) and “no” as being fully out of the set (fuzzy set value 0). Since two factors were highly skewed to the left, we adjusted the qualitative anchors relatively to their expression (Ext. Know-How, Third party R&D) following previous studies and recommendations (Pappas & Woodside, 2021; Plewa et al., 2016). For these conditions, we adjusted the threshold to 2 and 4, respectively (95% percentile) as full set-membership and 0 as full-non set-membership. As crossover points, we chose 1 and 2, respectively. For the remaining conditions, we chose as crossover point the mean of the factor (Int. InnoEx, Edu, Own R&D) or crisp set calibration if the factor was nominal (Coop, New Work, New BP). For the outcome, we chose three different calibrations, each representing one maturity stage. The qualitative anchors of these calibration values were chosen in several iterations, based on theoretical knowledge, the distribution of the underlying scale and data deviation, as well as the results of the NCA as indication for boundary conditions, representing logical ‘inhibitors’, which should be satisfied to proceed to the next level of maturity (Lasrado et al., 2016). Table 6 presents an overview of the calibrated factors.

After the data calibration, we proceed to obtain the solution terms that represent sufficient configurations of conditions for achieving a specific maturity level. Running the fs/QCA algorithm reveals 2^k possible combinations of *k* conditions which are displayed in a truth table. At this point, an analysis of all 10 conditions at the same time would have yielded 1.024 truth table rows, which cannot be empirically covered by our dataset of 224 cases. We, therefore, ran the analyses separately for the two dimensions, offering more possibilities to choose different paths for each maturity level independently for each dimension. The resulting truth table is sorted by frequency, which refers to the number of case-observations that are present for the combination of conditions. Since our data sample has more than 150 cases, the suggested frequency threshold is at least 3 (Fiss, 2011; Ragin, 2008). This ensures a fixed minimum number of observed combinations for the analysis. The lower the frequency cut off the more combinations of conditions will be considered in the analysis, resulting in more possible solution pathways, making the MM more complex in its application. The developer should, therefore, consider a threshold which reflects a meaningful representation of the target group’s data base. Thus, we followed

Fiss's (2011) and Ragin's (2008) suggestion whenever possible. However, not many companies reached a high level of maturity in our sample; thus, a higher frequency threshold would have meant a loss of these cases. To account for this on these specific occasions, we set the frequency threshold to 2 or 1. Since the consistency threshold refers to *"the degree to which cases correspond to the set-theoretic relationships expressed in a solution"* (Fiss, 2011). We set the consistency threshold at a minimum of 0.8, over the recommended minimum 0.75 (Ragin, 2006). The qualitative character of fsQCA allows for adjustments in the process of the cut-off choice, based on the characteristics of the underlying dataset.

We proceeded our analysis by deciding on which of the cases are fully representing the presence of the outcome (labelled 1) and which should be dismissed for the analysis (labelled 0). We did so by also taking the PRI consistency into account. This "Proportional Reduction in Inconsistency" reveals whether a condition is a subset of the presence and absence of the outcome at the same time (Schneider & Wagemann, 2012). A high PRI consistency represents very different consistency scores for the presence and absence of the outcome, which is why we only chose these combinations of conditions, that showed a high consistency and a high PRI consistency (>0.5) at the same time (Greckhamer et al., 2018; Pappas & Woodside, 2021). The calibration of the data and the following analysis is an iterative process, where the researcher needs to question and justify the results for accuracy. If needed, the calibration or thresholds need to be adjusted.[8]

Following these decisions, three different kinds of solutions are generated (complex, parsimonious, intermediate). We used the intermediate solutions in combination with the parsimonious solution for more detailed and aggregated solutions (Fiss, 2011), containing all logical remainders based on easy counterfactuals (Schneider & Wagemann, 2012).

3.7 Maturity Patterns

Concept

The derivation of maturity patterns is crucial for the structure of the model and the corresponding evolution paths. Such a maturity pattern represents the abstraction of NCA and fsQCA analysis results and consists of the sum of different configurations per maturity level. Since the analysis of necessity and sufficiency which is conducted by NCA and fsQCA is run for each maturity level separately, the structure of maturity levels as stages only becomes apparent after the analysis have been carried out and the results have been consolidated. Thus, a maturity pattern represents the abstraction of a maturity level with the number of configurations characterizing the respective level.

In a first step, the method NCA is applied on the dataset to test for necessary conditions which need to be present for the occurrence of a specific level of the outcome. The necessity of a specific factor for the occurrence of a specific level of the outcome can be interpreted as a given critical condition which is required in a company in order to be considered as having reached the respective maturity level.

Besides the identification of sufficient conditions, which lead to the occurrence of the outcome, the fs/QCA software also provides the possibility to test for necessary conditions. However, since the test for necessity in fs/QCA is different than the analysis in NCA, it can be understood as a useful complementation to run both necessary analyses. Whereas NCA distinguishes between a necessity of a certain level of the variable for a certain level of the outcome ("necessity in degree"), fs/QCA analyzes if the presence of a condition is in general necessary for the occurrence of the outcome ("necessity in kind") (Vis & Dul, 2018). The test for necessity in fs/QCA revealed no necessary conditions in the underlying data, thus, no single condition is on its own necessary for the occurrence of maturity level.

Instantiation

Table 7 and Table 8 present the results of the configurational analysis with fs/QCA with black circles indicating the presence of a condition and circles with "x" indicating its absence. Large circles (●) and bold circles with "x" (⊗) indicate core conditions; small and non-bold ones (•,⊗) peripheral conditions; blank spaces "do not care" situations (Fiss, 2011). As suggested by Pappas and Woodside (2021), we clarify the distinction between the absence of a condition and a "do not care" condition in our

[8] When rerunning the fsQCA with lower consistency cut-offs, same or similar configurations were achieved (see supplementary material). Notably, this led to an increase in overall solution coverage but with a decrease in the overall solution consistency, sometimes under the 0.80 and closer to 0.75. A low consistency threshold reduces type II errors (i.e., false negatives), but increases type I errors (i.e., false positives), and vice versa (Dul, 2016). Thus, we present the truth table, which can help increasing the validity of the findings and strengthen the rigorousness of the process.

interpretation. The absence of a condition is also referred to its negation or its opposite, i.e., the absence of a "high level" of a condition represents the "not-high level" of the respective condition. For readability reasons, we refer to this as low-level. Whereas the presence or absence of a "do not care" condition is irrelevant for the occurrence of the outcome. Next to the frequency (F) and consistency (C) thresholds, the tables show the consistency and coverage values of each solution term as well as for each maturity level. Consistency reveals to what degree the empirical case data is in line with the solution term. Coverage explains the relation in size between the solution term and the outcome. Furthermore, the displayed values reveal the percentage of the outcome, which is explained by a sufficient solution term that is part of a solution set (raw coverage) as well as the percentage of the outcome, which is uniquely explained by a single solution term (unique coverage) (Ragin, 2008). The results show 12 solutions (4 low, 3 medium, 5 high maturity) for the organizational dimension (Table 7) and 9 solutions (4 low, 3 medium, 2 high maturity) for the knowledge dimension (Table 8), revealing the existence of multiple solutions per maturity level, thus allowing for equifinality within an MM. The interpretation of the fs/QCA results is illustrated only for the organizational dimension. Table 8 for the knowledge dimension is to be paraphrased accordingly.

Table 7. Organizational Configurations Leading to Low, Medium, and High IC Maturity

	Low Level				**Medium Level**			**High Level**				
Organizational	F:3 ; C:0.956				F:4 ; C:0.888			F:1 ; C:0.914				
	1o	2o	3o	4o	5o	6o	7o	8o	9o	10o	11o	12o
New Work	**⊗**	**⊗**	●	**⊗**	⊗		⊗	●	⊗	**⊗**	●	**⊗**
Own R&D	**⊗**			**⊗**	●	●	**⊗**	**⊗**	**⊗**		•	⊗
Cont. R&D	●	•	●	●	●	●	●	●	●	●	•	**⊗**
Dev. of InnoEx	⊗	**⊗**	●	•		•	⊗		●	**⊗**		●
New BP		●	•	⊗	●	●	⊗	**⊗**	**⊗**	●	•	●
Third party R&D	⊗	⊗	⊗	•	⊗	⊗	⊗	⊗		**⊗**	●	⊗
Consistency	0.95	0.98	0.95	0.97	0.92	0.88	0.91	0.91	0.88	0.86	0.93	1
Raw Coverage	0.13	0.13	0.15	0.09	0.15	0.18	0.13	0.14	0.18	0.20	0.14	0.13
Unique Coverage	0.04	0.03	0.09	0.02	0.04	0.07	0.06	0.03	0.06	0.07	0.03	0.01
Overall solution cons.	0.944				0.886			0.805				
Overall solution cov.	0.278				0.280			0.335				

Note: Black circles indicate the presence of a condition, and circles with "x" indicate its absence. Large circles and bold circles with "x" indicate core -, small ones, peripheral conditions. Blank spaces indicate "do not care" conditions.

Organizational dimension (solutions 1o-12o, Table 7): Four paths lead to low maturity (1o-4o). The presence of Cont. R&D as core condition when New Work and Own R&D are absent will result in low maturity when either Dev. of InnoEx and Third Party R&D are absent, regardless of New BP (1o) or combined with the presence of Dev. of InnoEx and Third Party R&D when New BP is absent (4o). As well as the presence of New BP as core condition and Cont. R&D, when New Work, Dev. of InnoEx, and Third Party R&D are absent (2o). Finally, the presence of New Work, Cont R&D, high Dev. of InnoEx as core conditions and new BP will lead low maturity when Third party R&D is absent, regardless of Own R&D (3o). For medium maturity, 3 paths exist (5o-7o). The presence of Cont. R&D results in medium maturity when all other conditions are absent (7o). Also, given the absence of Third Party R&D, the presence of a high proportion of Own R&D, Cont. R&D, and New BP will lead to medium maturity either if New work is absent (5o) or if Dev. of InnoEx is present (6o) regardless of the other conditions. High maturity is characterized by 5 solution terms (8o-12o). The presence of New Work and Cont. R&D when Own R&D, New BP, and Third party R&D are absent (8o) as well as the presence of Cont. R&D and Dev. of InnoEx when New Work, Own R&D and New BP are absent lead to high maturity, regardless of the other two conditions in this dimension (9o). Further, when New Work, Dev. of InnovEx, and Third Party R&D are absent, high maturity can be reached by the presence of Cont. R&D and New BP, regardless of Own R&D (10o). Likewise, the presence of all conditions, except for Dev. of InnoEx. as "do not care" condition, leads to high maturity (11o), as well as the presence of Dev. of InnoEx. and New BP when all other conditions are absent (12o).

Table 8. Knowledge Configurations Leading to Low, Medium, and High IC Maturity

	Low Level				Medium Level			High Level	
Knowledge	F:4 ; C:0.87				F:2 ; C:0.879			F:2 ; C:0.855	
	1k	2k	3k	4k	5k	6k	7k	8k	9k
Int. InnoEx		●	•	⊗		⊗	●	●	●
Edu	⊗	●	⊗	•		⊗			●
Ext. Know-How	⊗	⊗	●	●	●	●	⊗	●	⊗
Coop	●		⊗	⊗	⊗		●	⊗	●
Consistency	0.86	0.89	0.95	0.97	0.86	0.91	0.86	0.9	0.85
Raw Coverage	0.15	0.21	0.07	0.09	0.17	0.13	0.15	0.15	0.17
Unique Coverage	0.07	0.14	0.01	0.02	0.05	0.02	0.08	0.06	0.08
Overall solution cons.	0.859				0.822			0.836	
Overall solution cov.	0.346				0.268			0.231	

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

3.8 Assessment Instrument

Concept

After having identified the respective maturity patterns per level, the researcher is able to develop the assessment instrument for a later application in an entity (i.e., a company).

Besides the previously determined characteristics of a small and industrial company, the ICMM can further only be applied with the conditions that were used for its development. Therefore, the researcher needs to build a questionnaire based on the same variables and scales that were used in the survey for the data collection (see Table 5).

Instantiation

In this example, the assessment instrument will consist of ten questions: four questions regarding the knowledge dimension and six questions regarding the organizational dimension. According to the anchor points from the calibration (see Table 6) the companies will be considered as being in, out, or neither in nor out of the conditions’ sets. The applicant of the assessment instrument will then be able to characterize the company regarding its present or absent conditions. Based on the existing maturity patterns (Table 7 and 8) and the respective entity’s characteristics, the applying researcher, e.g., the maturity model user, will be able to derive maturity paths, which represent prescriptive developmental states for the entity.

3.9 Maturity Paths

Concept

Besides the descriptive intention of the MM, the existing configurations of each maturity level can be used to derive recommendations for action regarding which conditions or factors should be focused on to achieve a higher maturity level (*prescriptive*). This process is dependent on the respective situation within the entity and is considered to be highly individual. Due to the concept of equifinality, an entity can choose—depending on its own characteristics—a corresponding path for increasing maturity.

Instantiation

Thus, the final step in the instantiation of the ICMM is the interpretation of the derived maturity patterns in order to provide the target group an overview and analysis of the fs/QCA results and the resulting maturity paths for improvement. We first present a dimensional interpretation and afterwards explain the interchangeability of maturity paths.

3.9.1 Dimensional Maturity Paths

For the qualitative dimensional interpretation of the maturity paths, we divide the description of the maturity per dimension and level. This analysis approach is intuitive since we ran the analysis for each dimension separately. Table 9 provides an overview of the different maturity pathways for each dimension as well as possible improvement paths that a company could take.

Table 9. Explanation of Maturity Pathways

	Low Maturity	Medium Maturity	High Maturity
Knowledge	A company can reach low maturity by: - only focusing on cooperations while not investing in external know-how and not investing in employees with a higher educational degree (1k) - focusing on internal innovation expenses and own educated personnel, given low external know-how (2k) - investing in external know-how and internal innovation expenses, with the absence of educated personnel and cooperation (3k) - focusing on own educated personnel and external know-how, with the absence of the remaining conditions (4k)	A company can proceed to medium maturity by: - investing in external know-how if it does not have cooperation (5k) - investing in external know-how if internal innovation expenses and education are low (6k) - investing in internal innovation expenses and cooperation but not external know-how (7k)	A company can reach high maturity by: - focusing on high external know-how and high internal innovation expenses, given the absence of cooperation (8k) - increasing internal innovation expenses, qualification of own staff, and cooperation but low external know-how (9k)
Organization	A company can reach low maturity by: - focusing on continuous R&D, no new methods of work organizations and high own R&D expenses (1o) - focusing on continuous R&D and the introduction of new business processes is sufficient when new work, increasing innovation expenses and third party R&D are absent (2o) - investing in continuous R&D, new work organizations and business processes as well as increase innovation expenses if only third party R&D is absent (3o) - increasing innovation expenses and third party R&D, as well as continuous R&D, when the remaining are absent (4o)	A company can proceed to medium maturity by: - investing in own R&D activities as well as new business processes but no new work or third party R&D (5o) - investing in own R&D activities as well as new business processes and increased innovation expenses but no third party R&D (6o) - focusing on continuous R&D (7o)	A company can reach high maturity by: - increasing eventually internal innovation expense but invest in continuous R&D in combination with new work organizations and the absence of remaining conditions (8o) - only increasing innovation expenses in the current year and investing in continuous R&D (9o) - investing in continuous R&D and in an introduction of new business processes (10o) - relying of third party R&D in combination with new work organizations, as well as new business processes and own continuous R&D activities (11o) - only investing in new business processes and an increase in innovation expenditure (12o)

When applying the ICMM to a company, the presented results offer the possibility to take the respective features regarding the present or absent conditions of that specific company into account. For example in the knowledge dimension, if a company reached low maturity by focusing on cooperation (1k), it can proceed to medium maturity by only investing in external know-how and keeping these cooperations, since it is a “do not care” condition (6k). Furthermore, if a company already focusses on internal innovation expenses and cooperations but does not invest in educated personnel since it is a don-not-care condition (7k) it can move to the highest maturity level by starting to exploit educated personnel (9k) and thus, being less dependent on external know-how, which may be relevant for intellectual property rights or patents.

Since there is no core presence of own R&D activities on the low maturity level in the organizational dimension, the configurations can be regarded as prerequisites for the development of the company structure that enables the development of innovative products in the next levels. For instance, solution 2o can be considered as a focus on the preparation or the alignment of the internal organizational structure to IC as it only focuses on the creation of new business processes and continuous R&D activities. Solution 4o can be interpreted as a focus on the improvement of existing or the creation of new products since the internal organizational structure is not affected. Solutions 5o and 6o appear in combination with the absence of third party R&D, thus, a strong focus on the company's actual product innovation activities can be assumed, when moving to the medium maturity level. It can be interpreted as an orientation towards the innovation of new products after having aligned the company's structure on the previous maturity level. Finally, solution 12o reveals that even on the high maturity level, companies still tend to adapt their process structure to changing requirements and need to increase their innovation expenditures.

3.9.2 Interchangeability of Maturity Paths

Due to the configurational development approach of the ICMM and the usage of the same outcome variable for the knowledge as well as organizational dimension, the MM offers the opportunity for a company to reach high maturity by focusing on the solution terms described in both dimensions as well as focusing exclusively on the knowledge dimension *or* the organizational dimension. Since the same dataset was used and all cases have values for each condition, both dimensions must be explained within the underlying data. We, therefore, investigated the calibrated data of the 224 cases and analyzed their membership values in each of the 12 solution terms. Thus, we identify companies with high values in solutions of either the knowledge or organizational dimensions as well as in both. Additionally, by going back into the raw data, we were able to analyze and interpret the underlying characteristics of the companies to explain their decisive situations.

Plotting the solutions against the outcome reveals the distribution of the cases (dots) and their membership values (Figure 7). Cases in the top right corner represent a high membership value in the solution 2k as well as in the outcome of low maturity.

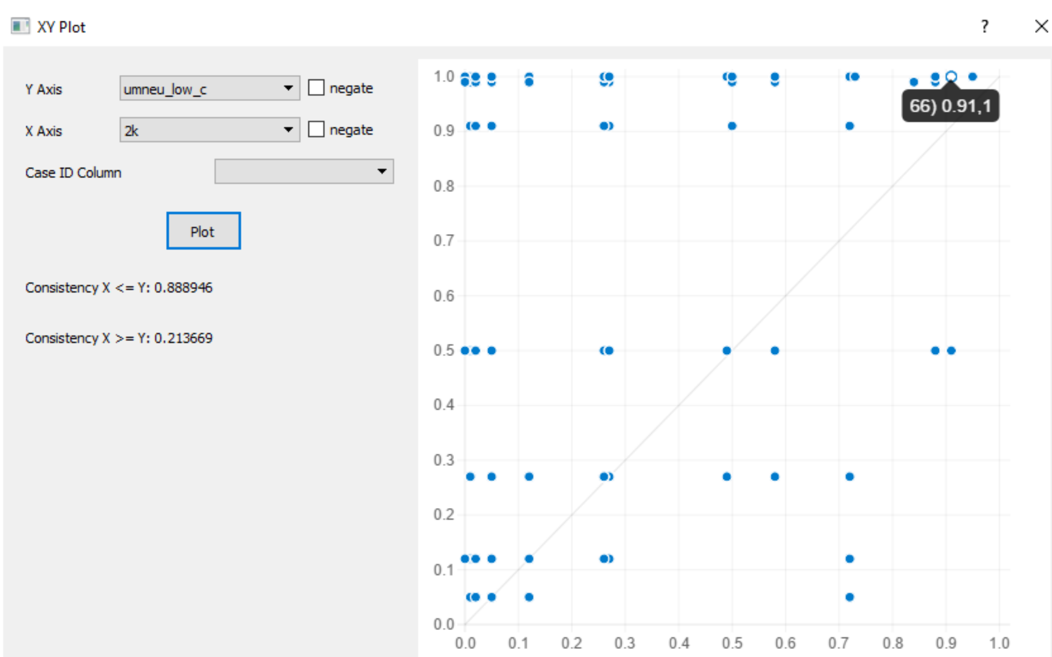

Figure 7. Fuzzy XY Plot of Solution 2k Against the Outcome of Low Maturity

When selecting single cases, for instance case 66 with a membership value of 0.91 in solution 2k and 1.0 in the outcome low maturity, it is possible to check and compare its membership values in the remaining solutions (Table 10). As the table shows, the argument of focusing on one dimension, in this case knowledge, is valid. Going back to the raw data reveals that company 66 indicated a proportion of total turnover from new or clearly improved products of 30 to 50%, which equals a 6 on scale 2. It, therefore, has membership values of 0.5 in the set of high, 0.95 in the set of medium, and 1 in the set of low maturity.

Table 10. Membership Values of Case 66 in all Solutions

Case 66	Knowledge Dimension											
Solution	1k	2k	3k	4k	5k	6k	7k	8k	9k			
M. Value	0.05	0.91	0.05	0.05	0.05	0.05	0.91	0.05	0.91			
Case 66	**Organizational Dimension**											
Solution	1o	2o	3o	4o	5o	6o	7o	8o	9o	10o	11o	12o
M. Value	0.27	0.05	0.05	0.05	0.05	0.05	0.27	0.05	0.27	0.05	0.05	0.05

Table 10 shows, that those maturity levels are mostly explained on the knowledge dimension. Furthermore, it reveals the evolutionary structure of an MM, which is implied by the fact that a company, which has reached the highest maturity, also has membership values in the lower maturity levels.

Table 11. High Membership Solutions of Case 66 per Maturity Level in the Knowledge Dimension

Knowledge	Low	Med.	High
	2k	7k	9k
Int. InnoEx	●	●	●
Edu	●		●
Ext. Know-How	⊗	⊗	⊗
Coop		●	●
Consistency	0.89	0.86	0.85
Raw Coverage	0.21	0.15	0.17
Unique Coverage	0.14	0.08	0.08

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

Analyzing the case’s configurations shows the following possible evolution path for a company (Table 11): in order to be considered on the low maturity level, the company needs to focus on high internal innovation expenses in combination with high investments in own educated personnel, while not investing in/focusing on external know-how (2k). It will proceed to medium maturity by suspending the focus on educated employees but continue investing in internal innovation expenditure as well as initiating cooperation with other firms (7k). The company will reach high maturity by investing in own educated personnel again as well as keeping its focus of the medium level (9k). Another possibility could be, that it invests immediately from the low maturity level into the required conditions representing 9k/high maturity. Thus, if there are sufficient financial resources, the company could, instead of gradually working its way up to the required conditions of the highest level, invest directly in all the required conditions for high maturity and thus skip the medium level.

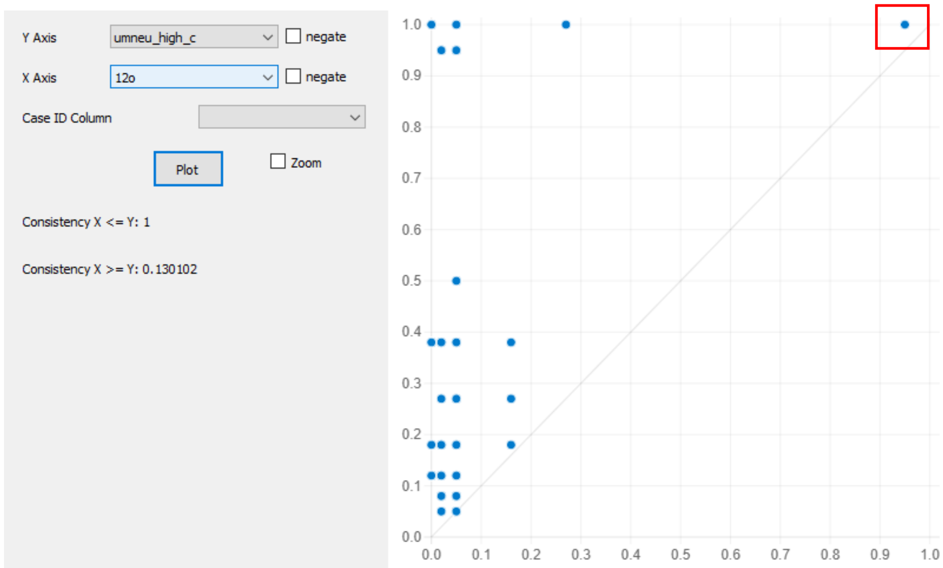

Figure 8. Fuzzy XY Plot of Solution 12o Against the Outcome of High Maturity and Case 84 (highlighted)

On the other hand, there exist companies, whose maturity may be explained by both dimensions. Case 84, for instance, has a membership value of 0.95 for the knowledge dimension, in solution 2k for low maturity, in 7k for medium maturity, and 9k for high maturity. Furthermore, this company has a 0.95 membership value in the high maturity configuration 12o of the organizational dimension (see Table 12 and Figure 8). Going back to the raw data reveals, that this company indicated a proportion of total turnover from new or clearly improved products of 75 to 100% (8 on scale 2), which is why this case has a membership value of 1 in each maturity level. However, the possibility of interdependencies of both dimensions as well as the influence of conditions that were not investigated in the fsQCA is still given.

Table 12. Membership Values of Case 84 in all Solutions

Case 84	**Knowledge Dimension**											
Solution	1k	2k	3k	4k	5k	6k	7k	8k	9k			
M. Value	0.05	0.95	0.05	0.01	0.05	0.01	0.95	0.05	0.95			
Case 84	**Organizational Dimension**											
Solution	1o	2o	3o	4o	5o	6o	7o	8o	9o	10o	11o	12o
M. Value	0.05	0.05	0.05	0.05	0.02	0.02	0.05	0.05	0.05	0.05	0.02	0.95

Besides the two-folded intra-dimensional maturity approach, interpreting those configurations reveals a possible inter-dimensional maturity path. Case 84 is a representative for a company's possibility to address the knowledge-related factors on the low and medium maturity level, and for the high maturity to either focus on the knowledge dimension as well (9k) *or* to focus on the organizational dimension instead (12o). However, the possibility of inter-dimensional maturity pathways should be regarded as a qualitative component of the maturation approach as the respective membership values of a case in each solution need to be considered and analyzed. A mathematical comparison or ranking between solutions of different fsQCAs is not possible, which is why the evaluation is the researcher's responsibility.

3.9.3 Testing for Predictive Validity

In order to examine the ability of the derived maturity paths to predict the dependent outcome variable, the derived solutions were tested for predictive validity (Gigerenzer & Brighton, 2009; Pappas & Woodside, 2021; Woodside, 2014). This procedure is important as it reveals the model's solution accuracy for different datasets not only the underlying one in this study. To do so the underlying dataset was randomly divided into a sub-sample and a holdout sample. Then, the data calibration was applied using the same qualitative anchors as above for both sets. Running fs/QCA on the sub-sample revealed several solution models which were afterwards computed as new variables for the holdout sample[9]. Plotting one of the model-variables against the outcome in the holdout sample reveals set-theoretic consistency scores (Ragin, 2018). Figure 9 resents the plot of one of the solution models "predmod1" against the outcome "low maturity" with the consistency scores of 0.82 and coverage of 0.34. If one of these scores is regarded as consistency it will automatically identify the other score as coverage. Predictive tests for the highly consistent model from the subsample (86%) also has a high predictive validity for the holdout sample (82%) (Figure 9). Thus, the argument is valid that the derived results have predictive validity for others, than the underlying data sample (Pappas & Woodside, 2021).

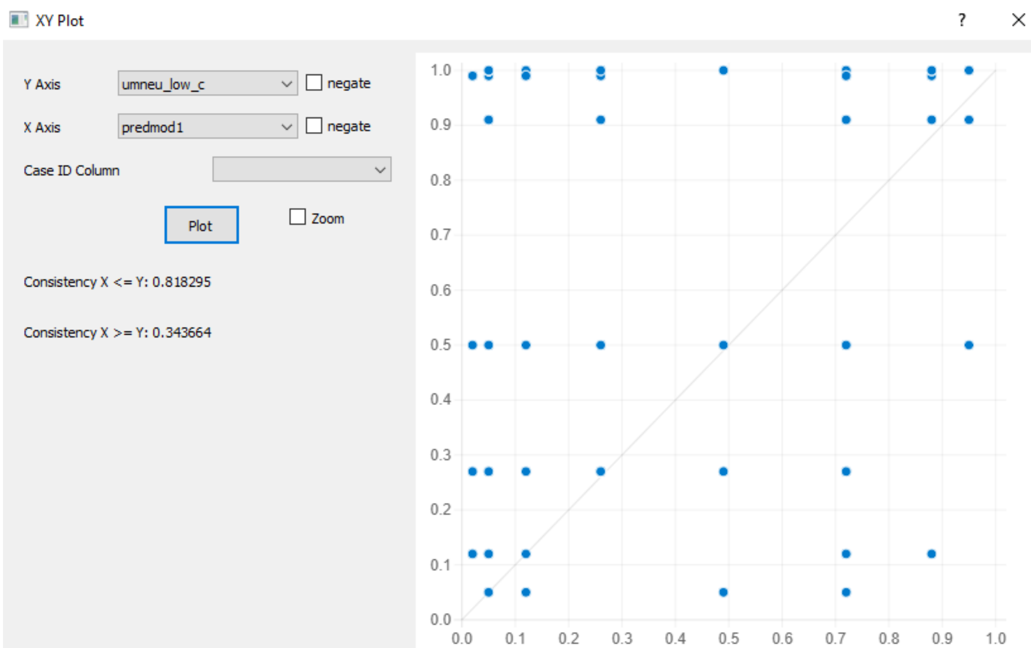

Figure 9. Fuzzy-Plot of "predmod1" on the Holdout Sample Data

4 Discussion and Implications

4.1 Discussion

When comparing the MM presented here with existing ICMM approaches, several differences can be found at a structural and content level. Although most ICMMs share the dominant structure of a staged MM, the concept of equifinality allows for a more fine-grained interpretation of the maturation process. By using an empirical development approach, which is based on a dataset of the target group itself, the resulting MM per se has a higher representativity than purely theory or literature-based (IC)MMs. This has implications for the validity but also the applicability of configurational-theory based MMs, as these MMs are individually valid for a previously defined class of entities and do not present an one-size-fits-all MM. In order to be able to run an fsQCA, the researcher needs to define a single outcome as dependent variable across all cases, thereby maturity is considered in relation to direct competitors, which creates a higher benchmark potential for the entity class, as the size and sector of a company can be decisive for its business model and processes. Whereas existing MM development approaches present guidelines for MM development (Becker et al., 2009; De Bruin et al., 2005), they do not present underlying theories and necessary concepts for the actual MMs in detail. Even though the development of the framework in Becker et al. (2009) is based on theoretical guidelines following design science research, the actual presentation of its instantiation remains on a generic level. However, this raises a common problem in presenting unified guidelines for research. On the one hand, the more general the description of the guidelines and the broader their applicability, the coarser the level of detail must be in order to be generally valid. On the other hand, the more detailed a process model is described, the more limited its application and the more difficult it is to replicate. We address this paradox by presenting a blueprint which

[9] More results of the testing for predictive validity can be found in the appendix.

is explained on a conceptual as well as an instantiation level. Thereby, we consider MMs first generally on a conceptual meta level and describe underlying components and relations, and second instantiate these components in an exemplary approach and present an actual MM for the domain of IC.

Our approach counteracts the criticism of ad-hoc development approaches (Felch & Asdecker, 2020; Pereira & Serrano, 2020). Further it exemplifies how NCA and fsQCA can be applied for the development of an ICMM and also explains the detailed analysis, which becomes possible due to the qualitative nature of fsQCA. Furthermore, drawing on the principle of equifinality, fsQCA offers the possibility of developing MMs that are characterized by a higher degree of individualization for the target group. The concept of inter- and intra-changeability of maturity paths takes the high demands of domain complexity and flexibility into account, providing applicants with a freedom of choice with regard to their maturation pathway. Also, the development process is characterized by choices for the researcher. For instance, if the researcher faces a scope of validity that is characterized by a high theoretical fragmentation, they have the possibility to divide the model into dimensions for a better depiction of factors, which belong to the same domain, however, are too fragmented in their underlying theoretical logic. If the scope of validity is defined by a group of factors that do not require further theoretical subdivision, the researcher can build the model unidimensionally. A configurational approach allows for both options.

A unidimensional development approach accounts for the configurational, thus, holistic logic, while the multidimensional development approach accounts for the classical MM logic as it considers the dimensional composition of factors, like many previous MMs. Still, both approaches are supported by fsQCA. The decision about a uni- or multidimensional MM depends on the underlying theoretical knowledge about the domain and needs to be explained by the author. Our MM development approach should be regarded as an exemplary instantiation of a multidimensional MM, which is aligned to existing MM structures (MM meta-model), applies fsQCA, and thereby provides a different approach to domain complexity by offering solutions for two different but domain-related dimensions.

Whereas Andersen et al. (2020) debate the focus on the 'empirical monolithic research culture' (p. 262) when it comes to a recommended development approach for MM, we agree with Poeppelbuss et al. (2011), that empirical approaches support the interpretability of the respective underlying logics of the model. MMs, which are built on quantitative development approaches, provide a traceable and reproduceable method, which can be verified and further validated. Furthermore, based on the characteristics of equifinality, a configurational theory-based approach addresses the criticism of MMs as oversimplifying reality and being merely 'step-by-step recipes' (McCormack et al., 2009), that lack empirical validity (De Bruin et al., 2005; King & Kraemer, 1984; Poeppelbuss et al., 2011), by providing more than one pathway to the state of full maturity.

Comparing the ICMM with existing approaches, it can be said that on a general level the results are in line with previous research. For example, both R&D and networks are important for SMEs at a low maturity level (Jørgensen & Ulhøi, 2010), and external networks and collaborations are needed to reach a high maturity level (Narcizo et al., 2019). However, especially in complex domains such as IC, the consideration of grouped configurations of maturity allows for a more accurate representation of an organization's reality. Compared to single IC factors, IC configurations are superior because they are able to represent different types of maturity pathways, whereas previous studies were not able to represent multiple maturity pathways, thus neglecting specific characteristics of the application class (Corsi & Neau, 2015; Jørgensen & Ulhøi, 2010; Narcizo et al., 2019; Zheng et al., 2021). By showcasing the instantiated ICMM, we address some of the criticism of existing ICMMs. For instance, by offering several solutions per maturity level, a company can decide which is the most convenient way to proceed in IC maturation. This is a major difference to previous ICMMs as the rarely present recommendation for reaching higher levels, and only depict a current IC level (Rush et al., 2007) or mention improvement areas without specifically describing practices (Enkel et al., 2011). Thus, the instantiation of our ICMM should be regarded as an extension of existing MMs in the domain of IC (Corsi & Neau, 2015; R. Narcizo et al., 2019), offering the possibility to provide a more individualized and diverse way to achieve full IC in SICs. Even though the presented ICMM is based on and valid for IC and the entity class of German SIC the applicability of such configurational theory-based MMs is not limited to any scope of validity, entity class or maturity matrix. Thus, further instantiations for e.g., middle or large companies in different regions or sectors are possible. However, the instantiation process would have to begin from the beginning and the data collection would have to be adapted accordingly to the scope of validity, the entity class, ant the maturity matrix.

4.2 Theoretical Implications

The theoretical contribution of this study is threefold. First, we contribute to existing MM research by offering an empirical, quantitative data-based development approach, which applies the configurational methods NCA and fsQCA. Differing from existing, merely ad-hoc and literature-based design approaches (Pereira & Serrano, 2020), this research addresses the call for a stronger embedding of theoretical and conceptual grounding in the development process of MMs (Andersen et al., 2020; Lasrado et al., 2016). We divide the development process into two levels: (1) the definition of conceptual MM characteristics, which are based on configurational theory, and (2) their exemplary instantiation in the domain of IC. Since we provide an extensive description of each characteristic as well as its instantiation in the domain of IC, we offer – apart from the ICMM – a blueprint for future configurational theory-based MM development approaches, that may be developed for different entity classes and domains.

Second, this paper contributes to the body of knowledge in IC maturity research by presenting 21 configurations of IC conditions representing different combinations of maturity paths for low, medium, and high IC of SICs. It, therefore, provides answers to the question of how a company identifies its own level of maturity and, depending on its own situation, on which conditions it should focus in order to improve its own maturity level. We, thereby, answer the call for research by Mendoza-Silva (2021) for ICMMs, which balance theory and practical applicability. The consideration of IC as configurations of antecedents rather than single factors has so far never received attention. However, the combination of NCA and fsQCA for MM development, as first done by Lasrado et al. (2016), in combination with more than one dimension, as demonstrated in our approach, offers a huge variety for possible maturation pathways. Even though our MM development approach applies the same idea of a configurational MM as Lasrado et al. (2016), we do not only provide pathways to low, high, and very high maturity by considering solutions leading to the absence or presence of the outcome, but we investigate three different outcome calibrations, thereby provide solutions for three maturity levels. Furthermore, our convergence of complexity by a dimensional subdivision allows for a more realistic depiction of the target group's characteristics – especially in domains that are theoretically fragmented in their underlying maturation knowledge. Thereby, the researcher can collect data which is entity class and dimension specific and can, thus, develop an MM with a more prescriptive character due to representative data and characteristics of its target group.

Finally, our approach extends the body of knowledge on the application of configurational methods. As highlighted by Mattke et al. (2021, 2022), most QCA applications in IS research neglect the combination of NCA and QCA. We fully agree with the authors as well as with Vis and Dul (2018), who further explain that complementing NCA with fsQCA will yield in more precise results as they can be analyzed "in degree" rather than just being "in" or "out" of a set. Especially in the context of MM development, this complementation is a fruitful addition as necessary conditions can represent maturity barriers and are therefore of crucial importance (Lasrado et al., 2016). Just as Lasrado et al. (2016), we encourage the development of MMs applying configurational methods, as the relative and dynamic concepts of MMs and their underlying domain can be depicted in a more flexible way than in existing deductively oriented development approaches.

4.3 Practical Implications

This study's findings have several implications for developers and users of a configurational theory-based MM. First, the MM developer is able to identify necessary (in kind and degree) as well as sufficient conditions and configurations, providing the possibility to derive explicit boundary conditions and bounding configurations, which define a certain level of maturity for a previously defined scope of validity. Second, due to the empirical and data-driven development approach a developer is able to derive MM families, representing a collection of MMs for different domains and entity classes as the respective target group. For instance, three MMs, each with an IC domain focus but derived for small, medium, and large companies separately, or three MMs, each with a focus on small companies but derived for three different sectors or domains.

The implications on the user level refer to the user's intention and thereby the MM's explanatory content. First, the here presented MM comprises characteristics of a descriptive and prescriptive MM simultaneously, which is relevant for its users, and requested by existing literature (Poeppelbuss & Roeglinger, 2011). An application as a *descriptive* MM reveals a company's IC maturity level based on the configuration of conditions that are present or absent. It will therefore represent a benchmarking tool, which can be applied in order to evaluate a company's relative maturity compared to companies of the same size and sector. The *prescriptive* application makes use of the concept of equifinality and offers a variety of different evolution paths. By applying fsQCA, the MM provides benchmark-specific solutions per maturity level, which can all be considered equal. Thus, no further quantitative decision calculus is needed for the best solution, as recommended, for instance, by Poeppelbus & Roeglinger (2011). Depending on the decisive situation and the presence or absence of relevant conditions, the MM offers a depiction of which configurations a company should address to proceed to a higher maturity level, taking their underlying business model into account. However, due to the intersections of the considered domains within a company (e.g., educated personnel is needed to carry out R&D) the conditions should not be considered as completely independent from each other, rather complementary. Finally, we contribute to the knowledge transfer problem raised by Van de Ven & Johnson (2006). By not only describing the proposed MM development approach at a theoretical and conceptual level but also instantiating and analyzing it with an existing dataset, we transfer research knowledge into practical knowledge by discussing and explaining its benefits in a context of practice. Given the conceptual blueprint character for a configurational theory and method-based MM development, this approach can, therefore, be applied by researchers as well as practitioners.

5 Conclusions and Limitations

The development of MMs has been a subject in research for many decades and still gives rise to challenges for researchers and practitioners. The contribution of this study is divided into a theoretical and a practical aspect.

First and primarily, by providing a rigorous development approach of a configurational theory-based MM, we provide a blueprint for future MM development, applying the same research methods, which has so far rarely been applied in IS research (Bley et al., 2021; Lasrado et al., 2016). Thus, our research contributes to the theoretical body of knowledge by offering structural components on a meta and instantiation level, which should be considered in order to develop a conceptually standardized and methodologically rigorous MM[10]. Second, by providing the empirically developed MM for SICs, we exemplarily present the concept of equifinality in an ICMM by identifying 21 different configurations of low, medium, and high IC maturity and contribute to practice by offering a company the possibility to choose its own, best suiting path to high maturity. Thereby we describe the advantages of configurational approaches for the development of MMs and how the combination of quantitative and qualitative analysis methods of fsQCA can benefit future MMs. This equifinality-based assessment approach addresses the call for better and theoretically grounded MMs that will lead to higher applicability (Andersen et al., 2020; Felch et al., 2019), as our findings specifically address the requirements of a particular class of entities, thereby making them more relevant for practice.

Like every research project, our approach has limitations. Due to the theoretical focus, the research approach lacks practical depth at some points, especially in the description of the methodological application of configurational theory. However, this is explained by the method itself as it strongly relies in its application on the researcher’s knowledge, perception, and the case-specific background. Therefore, the description of the fs/QCA application on our dataset may be subject to a personal bias and could be interpreted differently by researchers or practitioners from different fields.

Furthermore, as explained in 3.6.2 and given the freedom of choice of the researcher, a different calibration of the dataset is possible, resulting in different solutions. For example, Ragin (2000) recommends a frequency cut-off of about 10% for the entire sample. However, given the nature of an MM and our data sample, in which only a few companies have already reached the highest level of maturity, we had to adjust these frequency cut-offs in order to reflect a meaningful representation of the target group's database. Nevertheless, the calibration of the underlying dataset will always remain challenging and dependent on the knowledge of the researcher. Therefore, while we follow recommendations and established practices (e.g., Pappas & Woodside, 2021; Rihoux & Ragin, 2009; Schneider & Wagemann, 2012; Mattke et al., 2021), we calibrated values based on our own reasoning about the characteristics of the underlying entity class. Because we chose an existing database, we were bound by the scales and variables used. We adjusted the calibration anchors according to our knowledge and characteristics of the

[10] This study, however, should not be understood as a tutorial piece on how to apply fsQCA in detail. The reader is referred to the work of Pappas & Woodside (2021), Pappas & Bley (2023), Mattke et al. (2022), or Schneider & Wagemann (2010) for more detailed tutorials on how to conduct, run, and analyze fsQCA.

SICs, but these decisions may be biased – especially in light of the existing discussion in the (fs)QCA literature about the sensitivity and robustness of the results.

Another limitation of this study is the underlying dataset and its implication for the resulting maturity configurations. Although we focus on small companies, the investigated class of companies contains all sizes with less than 50 employees, which is why the implications for companies with fewer employees, i.e., micro-enterprises, could differ from the derived results. Our results – especially the solution coverage of 0.231 to 0.346 for the maturity levels – show that there are other factors, that might influence the IC of the companies investigated. However, the freedom of choice for the MM allows for such results, as long as the researcher can justify the selection and is aware of these restrictions.

Like Graeubig & Bley (2023), who present a further instantiation of this MM development approach for the domain of IC, future research should focus on the instantiation of fsQCA-based MMs in different domains as well as different entity classes. Whereas the method on how to develop a configurational MM is rigorous and consistent since the relational dependencies within the methodological constructs do not change; the MM as its instantiation needs to remain flexible and should be able to adapt to changes in the environment in which it is applied. Therefore, the proposed development approach for MMs can also be applied in any other domain than IC (e.g., IT, Business Processes), providing future developers of configurational MMs the possibility to follow the here proposed design and adapt it to any domain of interest.

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Appendix A: Detailed Comparison of the ICMM with Existing Approaches

Considering the results from the low maturity level, configuration 2k, 3k, or 4k can be interpreted as a focus on internal environment and daily operations (Narcizo et al., 2019). For instance, a focus on know-how in general (Corsi & Neau, 2015) is consistent with our results in the knowledge as well as organizational dimension, since for the performance of own R&D (1o-4o) know-how is a prerequisite. Configuration 1k on the low maturity level is in line with Jørgensen and Ulhøi (2010), who encourage the building of networks in SMEs, as they support IC and should therefore be formed at an early stage. The definition of a medium maturity level is rather generic in existing MMs. For instance, Corsi and Neau (2015, p. 63) define it as “Innovation is identified […] to stimulate coordination and frame the corresponding parameters and resources”. Narcizo et al. (2019) encourage a general focus on the integrated and holistic way of managing innovation activities within the companies. At that point, our results present a different approach as the configurations offer recipes of present and absent factors, therefore, they are prescriptive instead of providing merely descriptive information about the level of maturity. We were able to identify a rather significant difference to an existing MM on the highest maturity level. Configuration 11o reveals that it is possible for a SIC to reach a high maturity level by relying on third party R&D and not only by investing high amounts in own R&D. This is a presumably SME specific result and contradicts, for instance, Corsi and Neau (2015) who highlight a strong focus only on own R&D activities at the highest level of maturity. Similarities can be found in Narcizo et al.’s (2019) results as they highlight the importance of interaction with external agents being open and trustworthy, which is in line with our results 8k and 9k as they focus, among other factors, on external know-how or cooperation. Although Zheng et al. (2021) did not develop an MM, they investigated antecedents leading to high innovation performance in manufacturing firms of different sizes by applying fsQCA. Comparing their results with the highest maturity level of the ICMM reveals similarities in the knowledge dimension. They were able to identify that well-managed HR as well as governmental involvement in private and public R&D are core conditions in combination for high innovation performance. The ICMM configuration 9k shows a similar result as a focus on high educated personnel as well as cooperation with private and public institutions in combination with a high focus on internal innovation expenses will lead to a high IC maturity level. Of course, a direct comparison is only possible to a limited extent as both approaches investigated different companies and conditions. However, a broad similarity is discernible as both approaches highlight the focus on educated personnel as well as external support in daily operations.

The ICMM approach offers in total 4*3*2=24 (knowledge) and 4*3*5=60 (organizational) possible configurational combination pathways from low to medium to high IC maturity as well as 3*2=6 (knowledge) and 3*5=15 (organizational) configurational combination pathways from medium to high IC maturity. Furthermore, it might be possible for a company to evolve from the low level directly to the high maturity level by following 4*2=8 (knowledge) or 4*5=20 (organizational) possible evolution paths. Thereby our MM offers the possibility of a more individualized consideration of maturity within a company. Furthermore, it provides evidence, supported by the configurational logic, that our investigated outcome of interest is generated by a combination of several conditions rather than the presence of a single condition that is necessary or sufficient for the occurrence of the outcome.

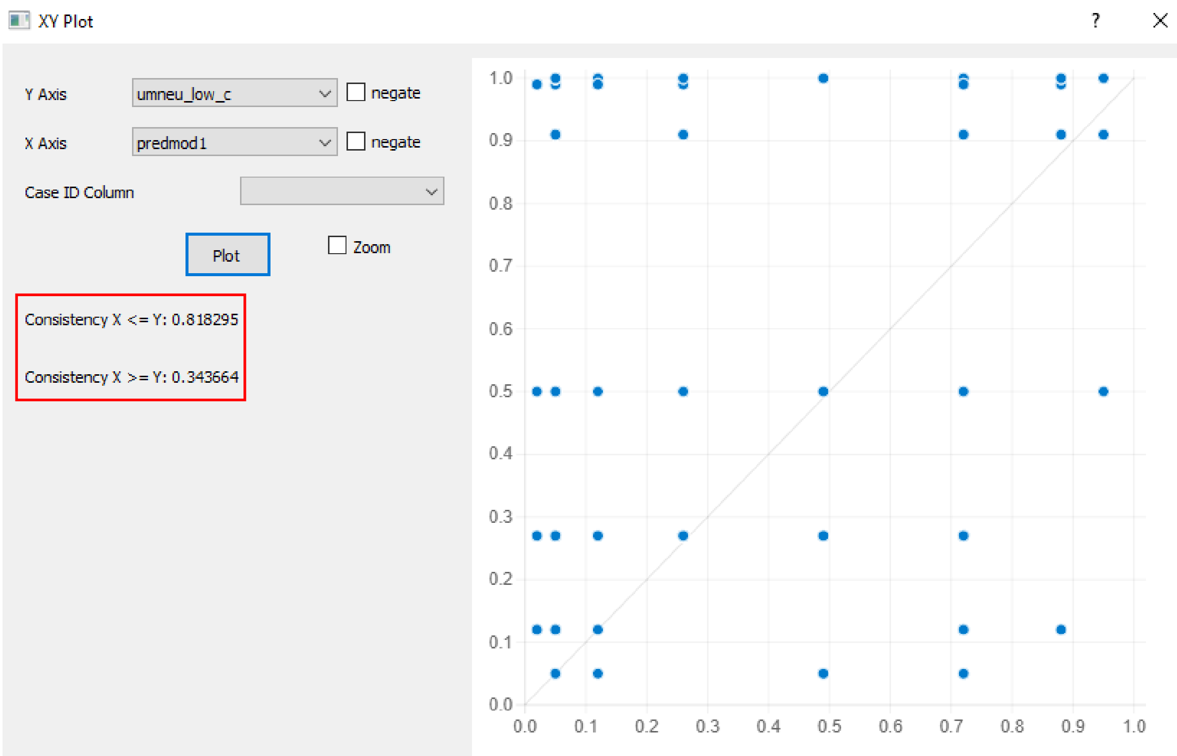
Appendix B: Results of the Predictive Validity Testing

Subsample1_random: Knowledge Dimension _ Low_Maturity:

```
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.837472
Assumptions:
                                   raw        unique
                                 coverage    coverage    consistency
                                ----------  ----------  ----------
Edu_c*~Coop_c                   0.355516    0.145552    0.860465
~ExtKnowHow_c*Coop_c            0.286477    0.151839    0.892791
IntInno_c*Edu_c                 0.257533    0.0111506   0.955967
~IntInno_c*~Edu_c*Coop_c        0.0952551   0.00545663  0.827835
IntInno_c*ExtKnowHow_c*~Coop_c  0.0953738   0.0151839   0.906426
solution coverage: 0.616607
solution consistency: 0.856907
```

Plot of Edu*~Coop (predmod1) with holdout sample:



Plot of the Model "Edu_c*~Coop_c" as "predmodel" in the holdout sample reveals Figure 10. The consistency scores 0.86 (subsample1) and 0.82 (holdout sample) as well as the coverage scores 0.36 (subsample1) and 0.34 (holdout sample) are largely consistent, revealing predictive validity of the derived solution models, as well as the derived results have predictive validity for others than the underlying data sample.

Appendix C: Truth tables and fs/QCA output

IntInno_c	Edu_c	ExtKnowHow_c	Coop_c	number	umneu_low_c	raw consist.	PRI consist.	SYM consist
0	1	1	0	4	1	0.970684	0.952076	1
1	1	0	1	8	1	0.949339	0.924155	0.956484
1	0	1	0	4	1	0.949264	0.912182	0.912182
1	0	0	1	6	1	0.930507	0.884793	0.885813
1	1	0	0	20	1	0.882353	0.830916	0.850486
0	0	0	1	14	1	0.874087	0.817648	0.836342
0	1	0	0	29	0	0.868769	0.822682	0.879437
0	1	0	1	31	0	0.839792	0.801794	0.840928
0	0	0	0	45	0	0.757267	0.672066	0.751578
1	0	0	0	32	0	0.744517	0.625626	0.694625

Figure 10. Truth Table of the Low Maturity Level of the Knowledge Dimension

IntInno_c	Edu_c	ExtKnowHow_c	Coop_c	number	umneu_medium_c	raw consist.	PRI consist.	SYM consist
1	1	1	0	2	1	0.980886	0.94086	0.94086
0	0	1	0	2	1	0.958092	0.874031	0.877432
1	0	1	0	4	1	0.946809	0.853933	0.853933
0	0	1	1	2	1	0.915441	0.730679	0.730679
0	1	1	0	4	1	0.915309	0.759704	0.813861
1	1	0	1	8	1	0.914648	0.840699	0.858341
1	0	0	1	6	1	0.879083	0.711921	0.737564
0	0	0	1	14	0	0.816004	0.641331	0.673876
1	1	0	0	20	0	0.808911	0.664835	0.689677
0	1	0	0	29	0	0.782982	0.650224	0.6924
0	1	0	1	31	0	0.764786	0.65956	0.714387
0	0	0	0	45	0	0.660611	0.46962	0.526584
1	0	0	0	32	0	0.656224	0.443265	0.468552

Figure 11. Truth Table of the Medium Maturity Level of the Knowledge Dimension

IntInno_c	Edu_c	ExtKnowHow_c	Coop_c	number	umneu_high_c	raw consist.	PRI consist.	SYM consist
1	1	1	0	2	1	0.949609	0.815873	0.815873
1	0	1	0	4	1	0.924714	0.722892	0.740741
1	1	0	1	8	1	0.854626	0.650795	0.713043
0	0	1	0	2	0	0.906512	0.563254	0.563254
0	0	1	1	2	0	0.894853	0.411523	0.413224
0	1	1	0	4	0	0.86645	0.524363	0.54327
1	0	0	1	6	0	0.825574	0.521905	0.556911
0	0	0	1	14	0	0.729083	0.36355	0.405751
1	1	0	0	20	0	0.683258	0.373278	0.409985
0	1	0	0	29	0	0.648969	0.316479	0.364914
0	1	0	1	31	0	0.615002	0.297643	0.371326
1	0	0	0	32	0	0.537454	0.210116	0.229787
0	0	0	0	45	0	0.508176	0.144978	0.169749

Figure 12. Truth Table of the High Maturity Level of the Knowledge Dimension

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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.874087
                                              raw        unique
                                            coverage     coverage     consistency
                                           ----------   ----------   ----------
~Edu_c*~ExtKnowHow_c*Coop_c                 0.154882     0.0736855    0.862129
IntInno_c*Edu_c*~ExtKnowHow_c               0.213669     0.140356     0.888946
IntInno_c*~Edu_c*ExtKnowHow_c*~Coop_c       0.0720095    0.014464     0.949264
~IntInno_c*Edu_c*ExtKnowHow_c*~Coop_c       0.092495     0.0244584    0.970684
solution coverage: 0.345707
solution consistency: 0.858883


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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.874087
                       raw        unique
                     coverage     coverage     consistency
                    ----------   ----------   ----------
ExtKnowHow_c         0.201627     0.082066     0.885014
~Edu_c*Coop_c        0.167111     0.0646844    0.837065
IntInno_c*Edu_c      0.239556     0.13508      0.896816
solution coverage: 0.418524
solution consistency: 0.843278


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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.874087
                                              raw        unique
                                            coverage     coverage     consistency
                                           ----------   ----------   ----------
~Edu_c*~ExtKnowHow_c*Coop_c                 0.154882     0.0736855    0.862129
IntInno_c*Edu_c*~ExtKnowHow_c               0.213669     0.140356     0.888946
IntInno_c*~Edu_c*ExtKnowHow_c*~Coop_c       0.0720095    0.014464     0.949264
~IntInno_c*Edu_c*ExtKnowHow_c*~Coop_c       0.092495     0.0244584    0.970684
solution coverage: 0.345707
solution consistency: 0.858883
```

Figure 13. fs/QCA Output of the Low Maturity Level for the Knowledge Dimension

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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.879083
                                     raw       unique
                                   coverage   coverage   consistency
                                  ---------- ---------- ----------
ExtKnowHow_c*~Coop_c               0.170321   0.0502997  0.861804
~IntInno_c*~Edu_c*ExtKnowHow_c     0.130188   0.0166149  0.905063
IntInno_c*~ExtKnowHow_c*Coop_c     0.146499   0.0802671  0.862439
solution coverage: 0.268038
solution consistency: 0.822011


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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.879083
                       raw       unique
                     coverage   coverage   consistency
                    ---------- ---------- ----------
ExtKnowHow_c         0.229346   0.142554   0.823706
IntInno_c*Coop_c     0.160079   0.0732874  0.849779
solution coverage: 0.302633
solution consistency: 0.808636


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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.879083
Assumptions:
                                     raw       unique
                                   coverage   coverage   consistency
                                  ---------- ---------- ----------
ExtKnowHow_c*~Coop_c               0.170321   0.0502997  0.861804
~IntInno_c*~Edu_c*ExtKnowHow_c     0.130188   0.0166149  0.905063
IntInno_c*~ExtKnowHow_c*Coop_c     0.146499   0.0802671  0.862439
solution coverage: 0.268038
solution consistency: 0.822011
```

Figure 14. fs/QCA Output of the Medium Maturity Level for the Knowledge Dimension

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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.854626
                                            raw       unique
                                          coverage    coverage    consistency
                                         ----------  ----------  ----------
IntInno_c*ExtKnowHow_c*~Coop_c           0.14929     0.0586734   0.90275
IntInno_c*Edu_c*~ExtKnowHow_c*Coop_c     0.172139    0.0815218   0.854626
solution coverage: 0.230812
solution consistency: 0.835743


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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.854626
                              raw       unique
                            coverage    coverage    consistency
                           ----------  ----------  ----------
IntInno_c*ExtKnowHow_c     0.170697    0.0561224   0.844213
IntInno_c*Edu_c*Coop_c     0.183119    0.0685449   0.821394
solution coverage: 0.239242
solution consistency: 0.792141


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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.854626
Assumptions:
                                            raw       unique
                                          coverage    coverage    consistency
                                         ----------  ----------  ----------
IntInno_c*ExtKnowHow_c*~Coop_c           0.14929     0.0586734   0.90275
IntInno_c*Edu_c*~ExtKnowHow_c*Coop_c     0.172139    0.0815218   0.854626
solution coverage: 0.230812
solution consistency: 0.835743
```

Figure 15. fs/QCA Output of the High Maturity Level for the Knowledge Dimension

NewWork_c	OwnRD_c	ContRD_c	Innovexp_c	NewBP_c	ThirdRD_c	number	umneu_low_c	raw consist.	PRI consist.	SYM consist
0	1	1	0	1	0	4	1	1	1	1
0	0	1	0	1	0	3	1	0.978451	0.963801	1
0	0	1	1	0	1	3	1	0.973011	0.954161	0.954162
1	0	1	1	1	0	3	1	0.969733	0.954667	0.954666
0	0	1	0	0	0	5	1	0.957043	0.929465	0.938683
1	1	1	1	1	0	10	1	0.955898	0.940361	0.955602
0	1	1	1	1	0	4	0	0.938164	0.909007	0.909007
1	0	1	0	1	0	3	0	0.931472	0.893805	0.89911
1	1	1	0	0	0	3	0	0.92483	0.877071	0.877072
1	0	0	0	1	0	6	0	0.900055	0.835862	0.950304
0	1	1	0	0	0	14	0	0.850768	0.796844	0.850526
1	0	0	1	0	0	3	0	0.849295	0.751226	0.77204
1	0	0	0	0	0	5	0	0.838752	0.741667	0.797312
0	0	0	1	0	0	11	0	0.835646	0.735453	0.867517
1	0	0	1	1	0	6	0	0.822743	0.713515	0.779527
0	1	1	1	0	0	18	0	0.791243	0.722702	0.773183
0	0	0	0	0	0	24	0	0.773433	0.685769	0.77086

Figure 16. Truth Table of the Low Maturity Level for the Organizational Dimension

NewWork_c	OwnRD_c	ContRD_c	Innovexp_c	NewBP_c	ThirdRD_c	number	umneu_medium_c	raw consist.	PRI consist.	SYM consist
0	1	1	0	1	0	4	1	1	1	1
1	1	1	1	1	0	10	1	0.934872	0.883806	0.891144
0	0	1	0	0	0	5	1	0.908103	0.764626	0.771067
0	1	1	1	1	0	4	1	0.888195	0.738304	0.776923
1	0	0	0	1	0	6	0	0.818035	0.553335	0.665064
1	0	0	0	0	0	5	0	0.806892	0.515498	0.565295
0	1	1	0	0	0	14	0	0.780933	0.636363	0.671574
1	0	0	1	1	0	6	0	0.75028	0.39704	0.450382
0	0	0	1	0	0	11	0	0.735604	0.485692	0.566253
0	1	1	1	0	0	18	0	0.707063	0.519907	0.562907
0	0	0	0	0	0	24	0	0.662784	0.468298	0.543931

Figure 17. Truth Table of the Medium Maturity Level for the Organizational Dimension

NewWork_c	OwnRD_c	ContRD_c	Innovexp_c	NewBP_c	ThirdRD_c	number	umneu_high_c	raw consist.	PRI consist.	SYM consist
0	0	0	1	1	0	1	1	1	1	1
1	0	1	1	0	0	1	1	0.968439	0.780348	0.780347
1	1	1	0	1	1	1	1	0.958449	0.765626	0.765626
1	1	1	1	1	1	1	1	0.951572	0.763486	0.763486
0	0	1	1	0	0	1	1	0.928665	0.596295	0.621621
0	1	1	0	1	0	4	1	0.92711	0.691057	0.910715
0	0	1	0	1	0	3	1	0.919865	0.619808	0.619808
0	0	1	1	0	1	3	1	0.916193	0.562962	0.628099
1	0	1	0	0	0	2	1	0.914063	0.551021	0.569621
0	1	1	0	1	1	1	0	0.938542	0.481482	0.511811
0	0	1	1	1	0	1	0	0.927748	0.465908	0.465908
0	1	1	1	1	1	1	0	0.92058	0.392156	0.461538
1	1	1	1	0	0	1	0	0.914414	0.30657	0.456523
1	1	1	0	0	0	3	0	0.892736	0.52788	0.577236
1	0	1	1	1	0	3	0	0.881306	0.566161	0.654135

Figure 18. Truth Table of the High Maturity Level for the Organizational Dimension

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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.955898
                                                             raw        unique
                                                           coverage    coverage    consistency
                                                          ----------  ----------  ----------
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~ThirdRD_c        0.134707    0.043454    0.951337
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c         0.126948    0.0332112   0.984593
NewWork_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c           0.154137    0.0867836   0.954267
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c*ThirdRD_c 0.0850458   0.020175    0.973011
solution coverage: 0.278415
solution consistency: 0.943615


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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.955898
                                raw        unique
                              coverage    coverage    consistency
                             ----------  ----------  ----------
~NewWork_c*~OwnRD_c*ContRD_c  0.185176    0.0895153   0.899307
~NewWork_c*~Innovexp_c*NewBP_c 0.153268   0.0540692   0.916142
NewWork_c*ContRD_c*Innovexp_c 0.19188     0.123285    0.946708
solution coverage: 0.366068
solution consistency: 0.895384


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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.955898
Assumptions:
                                                             raw        unique
                                                           coverage    coverage    consistency
                                                          ----------  ----------  ----------
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~ThirdRD_c        0.134707    0.043454    0.951337
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c         0.126948    0.0332112   0.984593
NewWork_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c           0.154137    0.0867836   0.954267
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c*ThirdRD_c 0.0850458   0.020175    0.973011
solution coverage: 0.278415
solution consistency: 0.943615
```

Figure 19. fs/QCA Output of the Low Maturity Level for the Organizational Dimension

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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.888195
                                                              raw       unique
                                                            coverage   coverage   consistency
                                                           ---------- ---------- ----------
~NewWork_c*OwnRD_c*ContRD_c*NewBP_c*~ThirdRD_c             0.146954   0.0383886  0.915407
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c             0.178211   0.0703283  0.884747
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c    0.126698   0.0623619  0.908103
solution coverage: 0.279645
solution consistency: 0.885845


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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.888195
                         raw       unique
                       coverage   coverage   consistency
                      ---------- ---------- ----------
~OwnRD_c*ContRD_c     0.310068   0.111828   0.833911
OwnRD_c*NewBP_c       0.270238   0.0106972  0.840094
ContRD_c*NewBP_c      0.362719   0.0323194  0.817964
solution coverage: 0.485244
solution consistency: 0.793943


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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.888195
Assumptions:
                                                              raw       unique
                                                            coverage   coverage   consistency
                                                           ---------- ---------- ----------
~NewWork_c*OwnRD_c*ContRD_c*NewBP_c*~ThirdRD_c             0.146954   0.0383886  0.915407
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c             0.178211   0.0703283  0.884747
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c    0.126698   0.0623619  0.908103
solution coverage: 0.279645
solution consistency: 0.885845
```

Figure 20. fs/QCA Output of the Medium Maturity Level for the Organizational Dimension

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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.914063
                                                                  raw       unique
                                                                coverage   coverage   consistency
                                                               ---------- ---------- ----------
NewWork_c*~OwnRD_c*ContRD_c*~NewBP_c*~ThirdRD_c                 0.144299   0.0286158  0.914909
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c                0.177352   0.0611132  0.880024
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c              0.197205   0.0715393  0.856043
NewWork_c*OwnRD_c*ContRD_c*NewBP_c*ThirdRD_c                    0.135759   0.0331631  0.929385
~NewWork_c*~OwnRD_c*~ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c     0.130102   0.0124223  1
solution coverage: 0.334738
solution consistency: 0.805015


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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.914063
                                                          raw       unique
                                                        coverage   coverage   consistency
                                                       ---------- ---------- ----------
NewWork_c*ThirdRD_c                                     0.173913   0.0455855  0.892431
NewWork_c*~OwnRD_c*ContRD_c*~NewBP_c                    0.146518   0.0133097  0.916089
~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c                   0.192658   0.0611132  0.871551
~NewWork_c*~ContRD_c*Innovexp_c*NewBP_c                 0.145076   0.0138642  0.951273
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c      0.197205   0.0665481  0.856043
solution coverage: 0.348602
solution consistency: 0.78087


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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.914063
Assumptions:
                                                                  raw       unique
                                                                coverage   coverage   consistency
                                                               ---------- ---------- ----------
NewWork_c*~OwnRD_c*ContRD_c*~NewBP_c*~ThirdRD_c                 0.144299   0.0286158  0.914909
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c                0.177352   0.0611132  0.880024
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c              0.197205   0.0715393  0.856043
NewWork_c*OwnRD_c*ContRD_c*NewBP_c*ThirdRD_c                    0.135759   0.0331631  0.929385
~NewWork_c*~OwnRD_c*~ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c     0.130102   0.0124223  1
solution coverage: 0.334738
solution consistency: 0.805015
```

Figure 21. fs/QCA Output of the High Maturity Level for the Organizational Dimension

Comparison of fs/qca results with lowered cut-offs

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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.839792
                                            raw       unique
                                          coverage    coverage    consistency
                                         ----------  ----------  ----------
Edu_c*~ExtKnowHow_c                       0.517971    0.0745547   0.821503
~ExtKnowHow_c*Coop_c                      0.348438    0.0761065   0.803578
~IntInno_c*Edu_c*~Coop_c                  0.258613    0.0207336   0.872095
IntInno_c*~Edu_c*ExtKnowHow_c*~Coop_c     0.0720095   0.0144638   0.949264
solution coverage: 0.637346
solution consistency: 0.806076


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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.839792
                   raw       unique
                 coverage    coverage    consistency
                ----------  ----------  ----------
Edu_c            0.594885    0.246695    0.830272
ExtKnowHow_c     0.201627    0.0388601   0.885014
Coop_c           0.398224    0.0754238   0.796894
solution coverage: 0.724502
solution consistency: 0.802903


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

File:
Model: umneu_low_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.839792
Assumptions:
                                            raw       unique
                                          coverage    coverage    consistency
                                         ----------  ----------  ----------
Edu_c*~ExtKnowHow_c                       0.517971    0.0745547   0.821503
~ExtKnowHow_c*Coop_c                      0.348438    0.0761065   0.803578
~IntInno_c*Edu_c*~Coop_c                  0.258613    0.0207336   0.872095
IntInno_c*~Edu_c*ExtKnowHow_c*~Coop_c     0.0720095   0.0144638   0.949264
solution coverage: 0.637346
solution consistency: 0.806076
```

Figure 22. fs/QCA Output of the Low Maturity Level for the Knowledge Dimension with Lowered Cut-Offs (Raw 0.840/Pri 0.802)

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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.808911
                                     raw       unique
                                   coverage    coverage    consistency
                                  ----------  ----------  ----------
ExtKnowHow_c*~Coop_c              0.170321    0.0795845   0.861804
~IntInno_c*~Edu_c*Coop_c          0.16539     0.0106972   0.800882
IntInno_c*Edu_c*~ExtKnowHow_c     0.240346    0.107883    0.818182
~Edu_c*~ExtKnowHow_c*Coop_c       0.17328     0.000455201 0.78922
IntInno_c*~ExtKnowHow_c*Coop_c    0.146499    0.00402096  0.862439
solution coverage: 0.430696
solution consistency: 0.765714


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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.808911
                      raw       unique
                    coverage    coverage    consistency
                   ----------  ----------  ----------
ExtKnowHow_c        0.229346    0.0892955   0.823706
~Edu_c*Coop_c       0.186405    0.067825    0.763993
IntInno_c*Edu_c     0.269555    0.145968    0.825703
solution coverage: 0.461877
solution consistency: 0.761476


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

File:
Model: umneu_medium_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.808911
Assumptions:
                                     raw       unique
                                   coverage    coverage    consistency
                                  ----------  ----------  ----------
ExtKnowHow_c*~Coop_c              0.170321    0.0795845   0.861804
~IntInno_c*~Edu_c*Coop_c          0.16539     0.0106972   0.800882
IntInno_c*Edu_c*~ExtKnowHow_c     0.240346    0.107883    0.818182
~Edu_c*~ExtKnowHow_c*Coop_c       0.17328     0.000455201 0.78922
IntInno_c*~ExtKnowHow_c*Coop_c    0.146499    0.00402096  0.862439
solution coverage: 0.430696
solution consistency: 0.765714
```

Figure 23. fs/QCA Output of the Medium Maturity Level for the Knowledge Dimension with Lowered Cut-Offs (Raw 0.809/PRI 0.665)

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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.825574
                                    raw       unique
                                  coverage    coverage    consistency
                                 ----------  ----------  ----------
IntInno_c*ExtKnowHow_c*~Coop_c   0.14929     0.0230701   0.90275
Edu_c*ExtKnowHow_c*~Coop_c       0.168589    0.0473602   0.857304
IntInno_c*~ExtKnowHow_c*Coop_c   0.195209    0.0996006   0.786066
solution coverage: 0.296251
solution consistency: 0.76533


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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.825574
                            raw       unique
                          coverage    coverage    consistency
                         ----------  ----------  ----------
IntInno_c*ExtKnowHow_c   0.170697    0.0227374   0.844213
Edu_c*ExtKnowHow_c       0.226819    0.0841837   0.812798
IntInno_c*Coop_c         0.206522    0.0866238   0.7499
solution coverage: 0.341504
solution consistency: 0.736427


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

File:
Model: umneu_high_c = f(IntInno_c, Edu_c, ExtKnowHow_c, Coop_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 2
consistency cutoff: 0.825574
Assumptions:
                                    raw       unique
                                  coverage    coverage    consistency
                                 ----------  ----------  ----------
IntInno_c*ExtKnowHow_c*~Coop_c   0.14929     0.0230701   0.90275
Edu_c*ExtKnowHow_c*~Coop_c       0.168589    0.0473602   0.857304
IntInno_c*~ExtKnowHow_c*Coop_c   0.195209    0.0996006   0.786066
solution coverage: 0.296251
solution consistency: 0.76533
```

Figure 24. fs/QCA Output of the High Maturity Level for the Knowledge Dimension with Lowered Cut-Offs (Raw 0.826/PRI 0.522)

Table 13. ICMM Knowledge Dimension

	Low Level				Medium Level			High Level	
Knowledge	F:4 ; C:0.87				F:2 ; C:0.879			F:2 ; C:0.855	
	1k	2k	3k	4k	5k	6k	7k	8k	9k
Int. InnoEx		●	•	⊗		⊗	●	●	●
Edu	⊗	●	⊗	•		⊗			●
Ext. Know-How	⊗	⊗	●	●	●	●	⊗	●	⊗
Coop	●		⊗	⊗	⊗		●	⊗	●
Consistency	0.86	0.89	0.95	0.97	0.86	0.91	0.86	0.9	0.85
Raw Coverage	0.15	0.21	0.07	0.09	0.17	0.13	0.15	0.15	0.17
Unique Coverage	0.07	0.14	0.01	0.02	0.05	0.02	0.08	0.06	0.08
Overall solution cons.	0.859				0.822			0.836	
Overall solution cov.	0.346				0.268			0.231	

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

Table 14. ICMM Knowledge Dimension with Lowered Cut-offs

	Low Level				Medium Level					High Level		
Knowledge	F:4 ; C:0.84				F:2 ; C:0.809					F:2 ; C:0.826		
	1k	2k	3k	4k	5k	6k	7k	8k	9k	10k	11k	12k
Int. InnoEx			⊗	•		⊗	●		•	●		●
Edu	●		●	⊗		⊗	●	⊗			●	
Ext. Know-How	⊗	⊗		●	●		⊗	⊗	⊗	●	●	⊗
Coop		●	⊗	⊗	⊗	●		●	•	⊗	⊗	●
Consistency	.82	.80	.87	.95	.86	.80	.82	.79	86	.90	.86	.79
Raw Coverage	.52	.35	.26	.07	.17	.17	.24	.17	.15	.15	.17	.20
Unique Coverage	.07	.08	.02	.01	.08	.01	.11	.00	00	.02	.05	.10
Overall solution cons.	0.806				0.766					0.765		
Overall solution cov.	0.637				0.431					0.296		

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.822743
                                                              raw       unique
                                                            coverage   coverage   consistency
                                                           ---------- ---------- ----------
NewWork_c*~OwnRD_c*~ContRD_c*~ThirdRD_c                     0.145819   0.0153329  0.700358
~NewWork_c*ContRD_c*~Innovexp_c*~ThirdRD_c                  0.278415   0.0720714  0.880793
NewWork_c*~OwnRD_c*NewBP_c*~ThirdRD_c                       0.177913   0.0387982  0.812359
~OwnRD_c*~ContRD_c*Innovexp_c*~NewBP_c*~ThirdRD_c           0.13061    0.0564281  0.779837
OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c            0.194053   0.0117946  0.83807
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c              0.153331   0.066112   0.930321
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c*ThirdRD_c  0.0850458  0.0194923  0.973011
solution coverage: 0.568626
solution consistency: 0.794587


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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.822743
                           raw       unique
                         coverage   coverage   consistency
                        ---------- ---------- ----------
NewWork_c                0.33323    0.0293003  0.760339
NewBP_c                  0.409274   0.0568625  0.809951
ContRD_c*~Innovexp_c     0.381836   0.167918   0.844337
~OwnRD_c*Innovexp_c      0.255695   0.0830589  0.775852
solution coverage: 0.736234
solution consistency: 0.780058


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

File:
Model: umneu_low_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 3
consistency cutoff: 0.822743
Assumptions:
                                                              raw       unique
                                                            coverage   coverage   consistency
                                                           ---------- ---------- ----------
NewWork_c*~OwnRD_c*~ContRD_c*~ThirdRD_c                     0.145819   0.0153329  0.700358
~NewWork_c*ContRD_c*~Innovexp_c*~ThirdRD_c                  0.278415   0.0720714  0.880793
NewWork_c*~OwnRD_c*NewBP_c*~ThirdRD_c                       0.177913   0.0387982  0.812359
~OwnRD_c*~ContRD_c*Innovexp_c*~NewBP_c*~ThirdRD_c           0.13061    0.0564281  0.779837
OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c            0.194053   0.0117946  0.83807
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c              0.153331   0.066112   0.930321
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c*ThirdRD_c  0.0850458  0.0194923  0.973011
solution coverage: 0.568626
solution consistency: 0.794587
```

Figure 25. fs/QCA Output of the Low Maturity Level for the Organizational Dimension with Lowered Cut-Offs (Raw 0.823/PRI 0.714)

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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.806892
                                                                    raw       unique
                                                                  coverage   coverage   consistency
                                                                 ---------- ---------- ----------
NewWork_c*~OwnRD_c*~ContRD_c*~Innovexp_c*~ThirdRD_c               0.129277   0.0488584  0.729454
~NewWork_c*OwnRD_c*ContRD_c*NewBP_c*~ThirdRD_c                    0.146954   0.0383886  0.915407
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c                    0.178211   0.0690387  0.884747
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c      0.126698   0.0475684  0.908103
solution coverage: 0.328503
solution consistency: 0.797862


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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.806892
                                 raw       unique
                               coverage   coverage   consistency
                              ---------- ---------- ----------
NewWork_c*~Innovexp_c          0.197557   0.0588727  0.689802
~OwnRD_c*ContRD_c              0.310068   0.100979   0.833911
OwnRD_c*NewBP_c                0.270238   0.0106972  0.840094
ContRD_c*NewBP_c               0.362719   0.0314847  0.817964
solution coverage: 0.544117
solution consistency: 0.748253


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

File:
Model: umneu_medium_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 4
consistency cutoff: 0.806892
Assumptions:
                                                                    raw       unique
                                                                  coverage   coverage   consistency
                                                                 ---------- ---------- ----------
NewWork_c*~OwnRD_c*~ContRD_c*~Innovexp_c*~ThirdRD_c               0.129277   0.0488584  0.729454
~NewWork_c*OwnRD_c*ContRD_c*NewBP_c*~ThirdRD_c                    0.146954   0.0383886  0.915407
OwnRD_c*ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c                    0.178211   0.0690387  0.884747
~NewWork_c*~OwnRD_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c      0.126698   0.0475684  0.908103
solution coverage: 0.328503
solution consistency: 0.797862
```

Figure 26. fs/QCA Output of the Medium Maturity Level for the Organizational Dimension with Lowered Cut-Offs (Raw 0.807/Pri 0.515)

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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.881306
                                                             raw       unique
                                                           coverage    coverage    consistency
                                                          ----------  ----------  ----------
NewWork_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c         0.14918     0.0263974   0.85019
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c           0.177352    0.0611131   0.880024
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c         0.197205    0.0715393   0.856043
NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~ThirdRD_c          0.180014    0.0545695   0.872112
NewWork_c*OwnRD_c*ContRD_c*NewBP_c*ThirdRD_c               0.135759    0.0225153   0.929385
~NewWork_c*~OwnRD_c*~ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c 0.130102   0.0124222   1
solution coverage: 0.387865
solution consistency: 0.771283


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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- PARSIMONIOUS SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.881306
                                                    raw       unique
                                                  coverage    coverage    consistency
                                                 ----------  ----------  ----------
NewWork_c*ThirdRD_c                               0.173913    0.0313884   0.892431
NewWork_c*ContRD_c*~Innovexp_c*~NewBP_c           0.151398    0.0263974   0.845201
~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c             0.192658    0.0611131   0.871551
~NewWork_c*~ContRD_c*Innovexp_c*NewBP_c           0.145076    0.0138641   0.951273
NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c            0.184894    0.0391524   0.856629
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c 0.197205   0.0665482   0.856043
solution coverage: 0.400842
solution consistency: 0.752603


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

File:
Model: umneu_high_c = f(NewWork_c, OwnRD_c, ContRD_c, Innovexp_c, NewBP_c, ThirdRD_c)
Algorithm: Quine-McCluskey

--- INTERMEDIATE SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.881306
Assumptions:
                                                             raw       unique
                                                           coverage    coverage    consistency
                                                          ----------  ----------  ----------
NewWork_c*ContRD_c*~Innovexp_c*~NewBP_c*~ThirdRD_c         0.14918     0.0263974   0.85019
~NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~NewBP_c           0.177352    0.0611131   0.880024
~NewWork_c*ContRD_c*~Innovexp_c*NewBP_c*~ThirdRD_c         0.197205    0.0715393   0.856043
NewWork_c*~OwnRD_c*ContRD_c*Innovexp_c*~ThirdRD_c          0.180014    0.0545695   0.872112
NewWork_c*OwnRD_c*ContRD_c*NewBP_c*ThirdRD_c               0.135759    0.0225153   0.929385
~NewWork_c*~OwnRD_c*~ContRD_c*Innovexp_c*NewBP_c*~ThirdRD_c 0.130102   0.0124222   1
solution coverage: 0.387865
solution consistency: 0.771283
```

Figure 27. fs/QCA Output of the High Maturity Level for the Organizational Dimension with Lowered Cut-Offs (Raw 0.881/PRI 0.528)

Table 15. ICMM Organizational Dimension

	Low Level				Medium Level			High Level				
Organizational	F:3 ; C:0.956				F:4 ; C:0.888			F:1 ; C:0.914				
	1o	2o	3o	4o	5o	6o	7o	8o	9o	10o	11o	12o
New Work	⊗	⊗	●	⊗	⊗		⊗	●	⊗	⊗	●	⊗
Own R&D	⊗			⊗	●	●	⊗	⊗	⊗		•	⊗
Cont. R&D	●	•	●	●	●	●	●	●	●	●	•	⊗
Dev. of InnoEx	⊗	⊗	●	•		•	⊗		●	⊗		●
New BP		●	•	⊗	●	●	⊗	⊗	⊗	●	•	●
Third party R&D	⊗	⊗	⊗	•	⊗	⊗	⊗	⊗		⊗	●	⊗
Consistency	0.95	0.98	0.95	0.97	0.92	0.88	0.91	0.91	0.88	0.86	0.93	1
Raw Coverage	0.13	0.13	0.15	0.09	0.15	0.18	0.13	0.14	0.18	0.20	0.14	0.13
Unique Coverage	0.04	0.03	0.09	0.02	0.04	0.07	0.06	0.03	0.06	0.07	0.03	0.01
Overall solution cons.	0.944				0.886			0.805				
Overall solution cov.	0.278				0.280			0.335				

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

Table 16. ICMM Organizational Dimension with Lowered Cut-offs

	Low Level							Medium Level				High Level					
Organizational	F:3 ; C:0.823							F:4 ; C:0.807				F:1 ; C:0.914					
	1o	2o	3o	4o	5o	6o	7o	8o	9o	10o	11o	12o	13o	14o	15o	16o	17o
New Work	●	⊗	●				⊗	●	⊗		⊗	●	⊗	⊗	●	●	⊗
Own R&D	⊗		⊗	⊗	•	•	⊗	⊗	●	●	⊗		⊗		⊗	•	⊗
Cont. R&D	⊗	●		⊗	●	•	•	⊗	●	●	●	●	●	●	●	•	⊗
Dev. of InnoEx		⊗		●	⊗	•	●	⊗		•	⊗	⊗	●	⊗	●		●
New BP			●	⊗	⊗	●	⊗		●	●	⊗	⊗	⊗	●		•	●
Third party R&D	⊗	⊗	⊗	⊗	⊗	⊗	•	⊗	⊗	⊗	⊗	⊗		⊗	⊗	●	⊗
Consistency	.70	.88	.81	.78	.84	.93	.97	.73	.92	.88	.91	.85	.88	.86	.87	.93	1
Raw Coverage	.15	.28	.18	.13	.19	.15	.09	.13	.15	.18	.13	.15	.18	.20	.18	.14	.13
Unique Coverage	.02	.07	.04	.06	.01	.07	.02	.05	.04	.07	.05	.03	.06	.07	.05	.02	.01
Overall solution cons.	0.795							0.798				0.771					
Overall solution cov.	0.569							0.329				0.388					

Note: Black circles indicate the presence of a condition, and circles with “x” indicate its absence. Large circles and bold circles with “x” indicate core -, small ones, peripheral conditions. Blank spaces indicate “do not care” conditions.

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