Relation between managerial cognition and industrial performance: An assessment with strategic cognitive maps using fuzzy-set qualitative comparative analysis

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Abstract

Strategic management researchers have long been fascinated with company performance in terms of underlying managerial cognition and its interpretation. This paper presents a methodology to examine the linkage between the cognition of individuals and company performance. We link cognitive maps with fuzzy-set qualitative comparative analysis (fsQCA) and examined the role of standard and newly proposed consistency and coverage formulas in the evaluation of social science data. We investigate the effect of cognitive diversity within a company, and between companies within an industry on company performance using experimental and real-life data. The proposed method used a cognitive mapping approach to elicit strategy frames from individuals in management teams and operationalized their cognitive diversity by distance ratios between individual- and group-level cognitive maps. The results highlight the different opportunities of cognitive diversity to the enhancement of company performance in the market and confirm the usefulness of new fsQCA consistency and coverage measures.

Keywords: Cognitive diversity, Cognitive map, Consistency, Coverage, Distance ratio, Performance

Relation between Managerial Cognition and Industrial Performance: An Assessment with Strategic Cognitive maps using Fuzzy-Set Qualitative Comparative Analysis

1. Introduction

The ultimate question of strategic management research is why some companies outperform others. One of the streams of research seeking answers to this question focuses on cognition in strategic management. Cognition in strategic management is often conceptualized in terms of strategic or cognitive frames, which represent cognitive construction strategies, and the key elements of strategy frames are their content and structure (Narayanan et al., 2011). Cognitive processes are used when people generate new knowledge, retrieve older knowledge from memory (where it has been stored in the form of knowledge structures), and apply knowledge (e.g., in decision-making). The concepts of strategic cognition and strategic frames refer to domain-specific cognitive structures and processes that are applied in a strategic decision-making context (Narayanan et al., 2011). Cognitive maps are mental representations of reality that include the central concepts of a domain at issue and the connections among these concepts. Causal maps are a subgroup of cognitive maps, essentially describing beliefs of the causal relationships among domain-specific factors. In this study, we approached cognition by means of cognitive-mapping techniques and used cognitive maps for the investigation of cognitive diversity and its effects on performance.

In order to take stock of this research of strategic cognition, scholars have presented reviews of this stream, see for example Kaplan (2011) and Narayanan et al. (2011). Kaplan (2011) organizes research on cognition and strategy in stages of 1) generating a 'proof of concept' (i.e., generating legitimacy for the line of inquiry), 2) assessing the accuracy of the managers' cognitive frames, 3) connecting cognition to strategic outcomes, and 4) building dynamic models of cognition in strategy making. When summarizing her review of research on the connection between cognition and strategic outcomes, Kaplan (2011, p. 680) states that this stream has shown "not only that managerial cognitive frames exist ('proof of concept') but that they matter." Narayanan et al. (2011), in turn, recognize five different streams within the cognitive perspective in strategy: 1) antecedents and outcomes of strategy frames, 2) determinants and consequences of strategy formulation, 3) cognitive construction of competitive/industry dynamics, 4) determinants and consequences of strategy implementation, and (5) antecedents and outcomes of organizational identity. They conclude their review on antecedents and outcomes of strategy frames by noting that the content of strategy frames is related to the context of the company (i.e., environmental, strategic, and organizational context) and that the structure of strategy frames matches the turbulence and dynamism of the environment. Thus, the extant knowledge finds that strategic cognition is linked to company performance. According to Gary and Wood (2011), diversity in cognition is generally seen as a source of heterogeneity in company strategies and performance. Yet, it is difficult to draw any generalizable conclusions about the nature of this relationship from the existing research. One way to approach this issue is to operationalize the cognitive frames and the diversity thereof by means of cognitive maps. Jenkins and Johnson (1997) find that the idiosyncratic details of the content and the structure of the cognitive maps explain the relationship between cognition and performance rather than the overall characteristics of the cognitive maps. These idiosyncratic details in Jenkins and Johnson's (1997) study were linkages that included concepts related to customers, actions and performance measures. Of course, these perceived causal linkages are not necessarily idiosyncratic (i.e., distinctive) in other contexts.

Thus, one of the main challenges in the study of the linkage between cognition and performance is that the idiosyncrasy or distinctiveness of content and the structure of cognition are highly dependent on the context in which the companies operate. This context dependency makes it difficult to accumulate evidence that is needed for drawing generalizable conclusions. Research on cognition in competitive or industry dynamics finds that competition, industry, and strategic groups within an industry are also cognitively constructed (Narayanan et al., 2011). This means that a cognitive context in the industry is formed by a company-level cognition that operates within the industry, and company-level cognition should be studied in relation to its cognitive context at an industry level when assessing its link to performance. Consequently, the kind of content and structure of the managerial cognition is idiosyncratic and distinctive and depends on the cognitive context at an industry level. In this paper, we studied this idiosyncratic nature of managerial cognition and its relationship to company performance by operationalizing the differences in the managerial cognition of the companies using their distance to the industry-level cognition represented by an industry-level cognitive map.

A diversity of managerial cognition can also occur within a company. Strategic management of a company is a complex task, which is often beyond the cognitive capabilities of one person (Bittner and Leimeister, 2014). In this context, diversity in cognition refers to cognitive diversity within decision-making groups, which is a necessity for the emergence of a wider horizon of opportunities for organizational renewal and monitoring in a competitive environment. However, a potential dark side of this cognitive diversity is that it may lead to difficulties in reaching consensus, which slows down decision-making and diminishes organizational responsiveness to environmental changes (Marcel et al., 2011). We examined the diversity of managerial cognition within the strategic decision-making group and its relationship to company performance by operationalizing the diversity as the average distance of decision-makers' cognitive frames (represented by cognitive maps) to the common company-level cognition (represented by a company-level cognitive map). Our findings contribute to the literature on cognition in strategic management.

The linkage between cognition and performance is inherently covered with uncertainty. So, in order to try to model it, we needed tools that can handle uncertainty. Fuzzy set theory is suitable area for such tools. Zadeh (1965) first introduced the concept of fuzzy sets that are able to operate under uncertainty. After his seminal paper, a great deal of mainly theoretical work was done in the 1970s and 80s, mostly in the United States, Europe. and Japan (Dubois and Prade, 1980; Klir and Yuan, 1995).

From the mid 1980s, applications started to play a larger role starting with fuzzy control and automation systems (Mamdani and Assilian, 1975; Takagi and Sugeno, 1985; Sugeno and Kang, 1988), but covering also other areas of artificial intelligence including, for example, machine learning (Bezdek, 1981). Fuzzy sets found their way in qualitative comparative analysis (QCA) by Ragin (1987), by the seminal work (Ragin, 2008, 2006, 2014). Fuzzy-set QCA (fsQCA) is gaining popularity in many fields not just sociology, although its use and also the development and critical assessment of the underlying methodology is still actively pursued in flagship journals in that field (see e.g., Vis and Dul, 2018; Baumgartner and Thiem, 2017; Braumoeller, 2017; Mikkelsen, 2017). Its growing popularity can be traced in practically all other fields of social sciences including strategic management and business research (Greckhamer et al., 2007; Skarmeas et al., 2014; Gabriel et al., 2018; Santos et al., 2018), organizational research (Meuer and Rupietta, 2016), and case studies (Schneider and Rohlfing, 2016; Mikkelsen, 2017). A special issue on set-theoretic methods in business has also recently been published in the *Journal of Business Research* (Roig-Tierno et al., 2016) with papers covering the use of fsQCA as well.

In this paper, we contribute to the line of research on the use of fsQCA in social sciences by investigating the usefulness of newly proposed consistency and coverage measures by Stoklasa et al. (2018, 2017) in a practical setting. We developed and present a methodology to study the linkage between cognitive diversity and performance. A recent research work (Wang et al., 2016) has revealed direct and indirect effects of cognitive diversity on team motivation and creativity. In the current study, the proposed method used a cognitive mapping approach to elicit strategy frames from individuals in the management teams. The cognitive maps were aggregated to company- and industry-level cognitive maps. The cognitive diversity of the companies was operationalized as the distance between the company-level cognition and the industry-level cognition, which related the company's strategic cognition to its cognitively constructed context. The effect of the within-company cognitive diversity on the company's performance was also studied. The links between cognition and performance were assessed with a fuzzy-set theoretic qualitative comparative analysis. We demonstrated the method with data from graduate students competing in teams in an eight-week business simulation task, which constituted a controlled experiment-like setting for the investigation of the links among various types of cognitive diversity and the performance of the companies. We also present the results calculated for data gathered through a survey from actual managers in the selected companies in a sustainability business context in Finland that constitutes a representative sample of the Finnish cleantech industry.

2. Data and methods

2.1. Data

The present study represented individual and shared cognitive structures (strategy frames) in the form of cognitive maps. Data were collected from two distinct sources: (1) a business simulation task in a controlled setting was repeatedly performed with graduate students of a business-oriented program (students represented virtual managers and formed managerial teams) and (2) a survey among the managers of a representative sample of the companies constituting the Finnish cleantech industry. Cognitive maps were extracted from both sources to represent the individual strategy frames. These maps were subsequently fused into a cognitive map representing a particular company (i.e., the strategy frame of the company or of the managerial team representing the company in the simulation task), and the diversity of the team (within-company diversity) was computed from these maps using two different distance ratios. The diversity among the companies within the industry was also assessed using the chosen distance ratios from the cognitive maps. After this, we examined the relation between performance and diversity using the fsQCA-based methods.

The shared cognitive map data from the strategic management teams, composed of graduate (Master's degree) students, were collected during an eight-week business simulation task on strategy implementation. The simulation was designed to help students understand and interpret the operations of international trading strategies in global business in a dynamic and competitive environment. The cognitive maps were developed based on 40 strategic-level constructs (see Table B.10 in the Appendix). From this list, each member of the group selected 12 constructs seen as the most relevant from his/her knowledge and unique views on the situation to create the cognitive maps. In the data, there were 431 individual-level cognitive maps which were produced at the beginning and end of the year (for three years: 2014, 2015, and 2016)[1]. For the purposes of this study, we

[1]Converted cognitive maps can be found from https://github.com/luukka76/

analyzed the cognitive diversity at the group (or company) level. To be able to do so, all the individual maps were converted into association matrices. The 40 strategic issues plus the total cumulative returns defined each dimension of the matrix (i.e., 41×41 association matrices were used to represent each individual map), and the average matrices for each group were then considered as a representation of the group (or company) level. To examine the relationship between cognitive diversity in the maps and the group (company) performance, the total cumulative shareholder return (TCSR; the 41st column/row in the matrices) was used as an indication of the group's performance.

Data collected from the companies followed the same structure as the student data. Nine cleantech companies from Finland were included in the study. In each company, the board of directors provided their interpretations on causal relations on economic, environmental, and sustainability issues. The number of members participating from each company varied from three to seven. To elicit the cognitive maps conceptualizing the strategic knowledge on the sustainability management, 50 strategic issues were considered. The company performance was measured using the net profit values that were collected along with other financial statistics of the selected companies. A detailed description regarding this data can be found in the publication of Bergman et al. (2020).

Cognitive-maps/blob/master/Cognitive_maps/Maps%20-%20data.zip

2.2. Introduction to cognitive mapping

The method of cognitive mapping is one of the most popular techniques for examining an individual's perceptional representations in strategic decision-making (Axelrod, 1976). A *cognitive map* is a map defined as a mental image representing the features of an environment (Kichin, 1994). A cognitive map can also be denoted by different names depending on the particular area of research (e.g., a causal map, cause-and-effect diagram, a strategy map, etc.). Cognitive mapping relates to an individual's daily life; it is a mechanism shaped by a series of continuous psychological transformations that include acquiring, coding, decoding, storing, and recalling information about its relative locations and attributes (Downs and Stea, 1973). A *directed graph* in graph theory (Bondy and Murty, 1976) has been used to describe the topology of a cognitive map. The directed graph consists of a set of vertices (nodes) and a set of directed edges (i.e., connections between pairs of nodes that have a clearly identified start- and end-node). The direction of an edge is usually denoted by an arrow. Robert Axelrod originally produced a directed graph including causal relations of an individual and referred to it as a cognitive map (Schneider and Wagemann, 2012). The nodes in the map represent the variables, and the edges with arrowheads indicate the directional (causal) relationships among the variables. The arrowhead represents the direction of the impact, or that one variable influences another. Cognitive maps can be represented by weighted directed graphs. In these weighted graphs, the edges are assigned numerical values (weights) that represent the strength of the assumed impact or influence.

The relationship between two cases (events represented by the nodes in the graph) such that one causes the other is defined as causality. In cognitive science, the causality is a critical aspect that plays a crucial role in decision-making and often supports choosing a course of action that seems best to achieve the expected outcomes (Carvalho and Tome, 2000). In the business simulation task with students, individuals were instructed to draw the cognitive maps by evaluating the impacts of each of the specific 12 strategic issues and TCSR (represented by nodes of the directed graph) on other selected strategic issues (that is, demonstrate the causal effect relations with strength and direction). The linkage (edge) between two nodes represented the direction of the effect, and its weight the strength of the causality. The effect might be positive (+) or negative (-), and its strength could be one (weak), two (moderate), or three (strong) (Gerard et al., 2004). In this case, positive and negative weights of edges were taken into account when an increase of the causal variable decreased the effect variable, and when an increase of the causal variable increased the effect variable, respectively. An example of a cognitive map, including positive and negative causal relationships between the elements with assigned strength values, is presented in Figure B.1.

[Figure 1 about here.]

In an organizational setting, cognitive mapping is an essential tool for managers who wish to develop complex systems in the fields of strategy (Kaplan and Norton, 2004; Marshall, 2013), quality (Evans, 2005), business (Ferreira et al., 2015, 2016) and information systems (Nelson et al., 2000).

Typically, managers or companies can apply cognitive maps to achieve organizational goals by identifying critical control points and root causes of a problem; they can also be used to guide risk management and communication strategies and identify causal relations in a complex system (Scavarda et al., 2006). However, those people are still suffering from a lack of tools and approaches in cognitive analysis. In this study, we intended to provide such a method for the analysis of the diversity of managerial cognition and for the examination of its relationship to the companies' performance.

2.3. Distance ratio measures for analyzing cognitive maps

The examination of the cognitive maps required measuring the cognitive diversity among the individual cognitive maps and also the diversity among the company-level cognitive maps and the industry-level one. We used the distance ratio (DR) as an estimator of cognitive difference between any pair of maps. The distance ratio is a value between 0 and 1, and when DR is 1, the distance between the maps is at its maximum; whereas when DR is 0, the maps are identical (Markoczy and Goldberg, 1995). In this research, we first employed the distance ratio formula originally used by Langfield-Smith and Wirth (1992, eq. 12), which can be stated as follows:

$$DR_1(A,B) = \frac{\sum_{i=1}^{p}\sum_{j=1}^{p}|a^*_{ij} - b^*_{ij}|}{6p_c^2 + 2p_c(p_{u_1} + p_{u_2}) + p_{u_1}^2 + p_{u_2}^2 - (6p_c + p_{u_1} + p_{u_2})} \quad (1)$$

where

$$a^*_{ij} = \begin{cases} +1 \text{ for } 0 < a_{ij} \text{ , } i \text{ or } j \notin P_c \\ -1 \text{ for } 0 > a_{ij} \text{ , } i \text{ or } j \notin P_c \\ a_{ij} \text{ otherwise} \end{cases} \quad \text{and } b^*_{ij} = \begin{cases} +1 \text{ for } 0 < b_{ij} \text{ , } i \text{ or } j \notin P_c \\ -1 \text{ for } 0 > b_{ij} \text{ , } i \text{ or } j \notin P_c \\ b_{ij} \text{ otherwise} \end{cases}$$

and A and B are two cognitive maps represented by their association matrices, p is the total number of possible nodes representing the strategic concepts in a map (p is the same for both A and B), P_c is the set of common nodes to both maps, p_c is the number of elements of P_c, p_{u_1} is the number of nodes unique to map A, p_{u_2} is the number of nodes unique to map B, and a_{ij} and b_{ij} are elements of the i^{th} row and j^{th} column in the association matrices relative to map A and B, respectively. Applying different distance ratio measures may provide other options for examining the cognitive structures. We also applied a new distance ratio measure that was recently introduced by Bergman et al. (2020) as an enhancement of the one presented in Equation (1). This generalization was presented by adding unit area information, in other words, d(x, y) = 1 cannot be exceeded, by taking into account the number of non-zero elements in both maps as follows:

$$DR_2(A, B) = \frac{\sum_{i=1}^{p} \sum_{j=1}^{p} |a^*_{i,j} - b^*_{i,j}| + |A_a - B_a|}{6p_c^2 + 2p_c(p_{u_1} + p_{u_2}) + p_{u_1}^2 + p_{u_2}^2 - (6p_c + p_{u_1} + p_{u_2}) + T_2} \quad (2)$$

where A_a and B_a are the counts of non-empty nodes in the cognitive map A and B, respectively and $T_2 = \max([A_a, B_a])$. The formulas of Langfield-Smith and Wirth (1992) and also Markoczy and Goldberg (1995) have been widely used by managerial and organizational cognition researchers and easier-to-use tools have been developed like cognizers (Clarkson and Hodgkinson, 2005) to do the analysis. Since we were also using the modified form from Bergman et al. (2020) and applying fsQCA, we used the MATLAB$^{\text{TM}}$ software and made our own codes to perform the analysis.

2.4. Fuzzy set-theoretic Qualitative Comparative Analysis

Our analytic approach was based on the fuzzy set-theoretic qualitative comparative analysis (fsQCA), as we already identified the expected outcome, input attributes, and cases and performed the first step involving the calculations of the distance ratios. fsQCA was initially introduced by Ragin (2000, 2008) and built upon fuzzy set theory for linguistics analysis from data which were connected with the cases. fsQCA is a powerful approach that applies a holistic perspective to acquire similarities and differences through the cases. In fsQCA, an analysis of a set of relations is produced that conceptualizes the arguments while keeping the uniqueness of the characteristics and makes comparisons between predictors and the outcomes (Haumann et al., 2015). Having identified which conditions are necessary or sufficient to produce the outcome, the fsQCA interprets causal relationships (cause-effect) between predictor and outcome (Skaaning, 2011). In the set-theoretic framework, the interpretations of set relations are often made in terms of necessary or sufficient conditions for the investigated outcome. Necessary and sufficient conditions for an outcome B can be investigated by examining the consistency and coverage of the relations $A \rightarrow B$ and $B \rightarrow A$ (this is inline e.g., with Schneider and

Wagemann (2012)). The consistency of $A \to B$ describes how much the data suggests that $A \subseteq B$, in other words, how plausible it is to assume that A is a sufficient condition for B. On the other hand, the consistency of $B \to A$ (which is identical with the coverage of $A \to B$) describes how much evidence there is in the data for $B \subseteq A$, in other words, how plausible it is to assume that A is a necessary condition for B based on the data. Various consistency and coverage measures are discussed in detail in the following sections. Using these measures, we intended to apply the fsQCA to evaluate relationships between various levels of cognitive diversity and performance. Before we explain the critical aspects of the fsQCA which were used in this analysis, let us first introduce the basic concepts and notations of fuzzy set theory, which were used throughout the study.

2.4.1. Basics of fuzzy set-theory

Fuzzy set theory was initially introduced by Zadeh (1965). A *fuzzy set* A is defined on a non-empty set (universal set) U by a mapping $\mu_A : U \to [0, 1]$, where μ_A is called a membership function of A. For any $x \in U$, the value $\mu_A(x) = A(x)$ is called a degree of membership of x to fuzzy set A. A fuzzy set usually integrates qualitative and quantitative assessments. For example, the qualitative terms "fully out" and "fully in" are represented by 0 and 1, respectively, and the values in between them represent the partial membership of a given observation in the fuzzy set. Moreover, there are many types of fuzzy sets that are characterized by different membership functions. A triangular-shaped membership function is the simplest and most common function in current applications. For the real parameters α, β, and γ such that $\alpha < \beta < \gamma$, the triangular membership function $\Lambda(x; \alpha, \beta, \gamma)$ is defined as:

$$\mu_A(x) = \Lambda(x;\alpha,\beta,\gamma) = \begin{cases} 0 & \text{if } x < \alpha \text{ or } x > \gamma \\ \frac{x-\alpha}{\beta-\alpha} & \text{if } \alpha \leq x \leq \beta \\ \frac{\gamma-x}{\gamma-\beta} & \text{if } \beta \leq\ x \leq \gamma \end{cases} \tag{3}$$

Moreover, a trapezoidal membership function $\Pi(x;\alpha,\beta,\gamma,\delta)$ that is formed by four input parameters α,β, γ, and δ such that $\alpha < \beta < \gamma < \delta$, is defined as follows:

$$\mu_A(x) = \Pi(x;\alpha,\beta,\gamma,\delta) = \begin{cases} 0 & \text{if } x < \alpha \text{ or } x > \delta \\ \frac{x-\alpha}{\beta-\alpha} & \text{if } \alpha \leq x \leq \beta \\ 1 & \text{if } \beta \leq\ x \leq \gamma \\ \frac{\delta-x}{\delta-\gamma} & \text{if } \gamma \leq\ x \leq \delta \end{cases} \tag{4}$$

Furthermore, fuzzy sets can be generated by using linguistic labels, for example, low, middle, and high, which describe a specific variable called a fuzzy variable (Klir and Yuan, 1995). We could say accordingly that the analysis in this study was based on the triangular fuzzy sets formed by linguistic levels on the distance ratios and performance measures. The cardinality of a fuzzy set A on a finite universal set U is $Card(A) = \sum_{x \in U} \mu_A(x)$, and on an infinite universal set U, it is $Card(A) = \int\limits_U \mu_A(x)dx$.

2.4.2. Consistency and coverage measures applied in the analysis

In the fsQCA, we can calibrate the variables (often addressed from the fuzzy sets) using the evidence from the cases and theoretical knowledge (Ragin, 2008). In the fsQCA, there are two essential notions, consistency and coverage. Let us assume that we are interested in the assessment of the causal relationship $A \rightarrow B$ using the data we have available. We can be interested in knowing whether A is a sufficient condition for B (this would correspond with $A \subseteq B$) and whether A is a necessary condition for B (which corresponds with $B \subseteq A$). Consistency provides a measure of evidence in favor of the investigated claim (e.g., $A \subseteq B$) in the data, in other words, it is dependent on the proportion of cases of A coinciding with B in all cases of A in the data. If the consistency score is low for a causal configuration, then the empirical evidence does not support the existence of the given causal configuration (alternatively, we can conclude that the presence of A is not sufficient for the outcome B to appear). The coverage of $A \rightarrow B$, on the other hand, indicates how many of the cases of the outcome B are explained by (associated with) A (Schneider and Wagemann, 2012). In contrast to the consistency of sufficient conditions, if the amount of coverage is low for a setting, this does not imply less relevance (Kane et al., 2014; Tierno et al., 2017).

In this analysis, we mainly focused on the consistency and coverage measures as defined by Ragin (2008), denoted with an F1 subscript, and their enhancements as proposed by Stoklasa et al. (2017, 2018), denoted with F2 and F4 subscripts. The original consistency and coverage measures are calculated in the following way:

$$Cons_{F_1}(A \Rightarrow B) = \frac{Card(A \cap B)}{Card(A)} = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} A(x_i)} \tag{5}$$

$$Cove_{F_1}(A \Rightarrow B) = \frac{Card(A \cap B)}{Card(B)} = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} B(x_i)} \tag{6}$$

where A and B are two fuzzy sets on a universal set $U = \{x_1, x_2, ..., x_n\}$. Here, we assume that $Card(A) \neq 0$ and $Card(B) \neq 0$ with respect to the relation $A \Rightarrow B$. When $A \cap B = A$, then $Cons_{F_1}(A \Rightarrow B) = 1$ (perfect consistency), and this means that there is no counter-evidence to the given relation $A \Rightarrow B$ in the data. On the other hand, $Cove_{F_1}(A \Rightarrow B) = 1$ indicates that only A is connected with B in the data (i.e., $B \subseteq A$). If there are other causes for B, the values of the coverage would be less than 1. In general, the idea must be to obtain a good balance in a situation where the solution is compelling both theoretically and empirically, and there are ranges of consistency and coverage scores that validate our solution. If we have very high consistency, but the coverage is low, then our solution is not compelling since that does not explain many cases at all (Elliot, 2013). On the contrary, if we have a very high coverage but with low consistency, then that is also not compelling because there is not enough evidence in favor of the case we evaluated.

Furthermore, while evidence is being explored in favor of or against $A \Rightarrow B$ using set-theoretical concepts, it would be an advantage to examine evidence simultaneously to $A \Rightarrow \bar{B}$, as suggested by Stoklasa et al. (2017). This way we can also take into consideration possible ambivalence in the data. To take counter-evidence into account, we can use the formulas for fuzzified consistency and coverage measures introduced in Stoklasa et al. (2017, 2018) and denoted with an F_2 subscript, which are defined as follows:

$$Cons_{F_2}(A \Rightarrow B) = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(A(x_i), B(x_i), \bar{B}(x_i))}{\sum_{i=1}^{n} A(x_i)} \quad (7)$$

$$Cove_{F_2}(A \Rightarrow B) = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(B(x_i), A(x_i), \bar{A}(x_i))}{\sum_{i=1}^{n} B(x_i)} \quad (8)$$

From the definition, the F_2 set-theoretic measures take values ranged in [0, 1] where 1 describes the clear evidence (no ambivalence, no counter-evidence) and 0 describes the cases in which all the data that provide evidence in favor of $A \Rightarrow B$ also provide at least as strong evidence in favor of $A \Rightarrow \bar{B}$ (Stoklasa et al., 2017). This property reduces the values of consistency and coverage, and considering all the measures together, they vary according to the following rules:

$$Cons_{F_1}(A \Rightarrow B) \geq Cons_{F_2}(A \Rightarrow B) \;\&\; Cove_{F_1}(A \Rightarrow B) \geq Cove_{F_2}(A \Rightarrow B) \quad (9)$$

To access the considerable amount of support that we can observe to the given relation and to reflect this in the values of the consistency and coverage measures, Stoklasa et al. (2017) also have suggested different versions of (7) and (8) as F_3 consistency and coverage measures (by reflecting the ambivalent evidence again and considering the pure counter-evidence of the investigated relationship in the data). Shortly after this, an updated version of these measures was suggested (Stoklasa et al., 2018) and denoted as F_4 consistency and coverage. Since the latter measures are an extension of the former ones, the F4 measures were considered further in this paper. Stoklasa et al. (2018) introduced the F_4 consistency and coverage measures in such a way that F_4 consistency higher than 0.5 supports the existence of a given relationship. To be more precise, $Cons_{F_4}(A \Rightarrow B) > 0.5$ implies that there is more evidence in favor of the given relationship $A \Rightarrow B$ than there is evidence in favor of

$A \Rightarrow \bar{B}$ in the data. In this study, we also employed F_4 measures [2] and their formulations were as follows:

$$Cons_{F_4}(A \Rightarrow B) = \frac{1}{2}\Big(1 + \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(A(x_i), \bar{B}(x_i))}{\sum_{i=1}^{n} A(x_i)}\Big) \tag{10}$$

$$Cove_{F_4}(A \Rightarrow B) = \frac{1}{2}\Big(1 + \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i)) - \min(B(x_i), \bar{A}(x_i))}{\sum_{i=1}^{n} B(x_i)}\Big) \tag{11}$$

2.5. Research setting

Our goal was to examine the impacts of the cognitive diversity on the company performance through the analysis of strategic interpretations in the cognitive maps. In addition to that, the research model was designed based on the information acquired from the cognitive maps where individuals' beliefs in a strategic operation have been asserted, and the performance measures observed. Initially, we assumed that the different levels of diversity of an individual's (managerial) cognition drive the company performance. Moreover, we specified these assumptions precisely (as described in the next section) to identify the different configurations of cognitive diversity that resulted in successful company performance. We also considered another source of cognitive diversity, the diversity on the company-industry level. The effect of this diversity (the difference of the

[2] Matlab functions for these measures can be found from https://se.mathworks.com/matlabcentral/fileexchange/63988-degree-of-support-disproof-consistencies-coverages

company strategic frame from the industry-level one) on the performance of the company was investigated in an analogous way as the within-company diversity effect.

2.5.1. Hypothesis models

Concerning the data samples, the argument initially built was that the distance ratio (diversity) between the strategic decision-makers within the company reflected the group performance. The purpose of this was to develop and test the hypotheses which determined the relations between cognitive diversity within the company and the company performance. Next, we also considered the distances from the group maps (simulating company-level strategy frames) to the class map (simulating the industry-level strategy frame), where the class map was created by aggregating all the group maps in a particular period in a year. This kind of aggregation has previously been introduced in Bergman et al. (2016). The company-level maps and the industry-level map were created in an analogous way with the real-life company data as well; the distance ratio from the company-level maps to the industry-level map was considered as the diversity among companies within an industry. In addition, for all the cases, we initially adopted professional linguistic levels (high, middle, and low) on the variables (DR and company performance) and proposed nine hypotheses, as described in Table B.1, to test the influences of the DR on the company performance. As an example, H_{01} in Table B.1 indicates that if the DR is low, then the company performance is hypothesized to also be low. Based on the available previous research on the effects of diversity on performance, we assumed that H_{03} and H_{09} would be supported by the data.

[Table 1 about here.]

2.5.2. Process of empirical assessment

The analysis of data started by creating group cognitive maps (i.e., the averaged cognitive maps from all the individuals' maps for each specific group). Such a group map is represented by an average adjacency matrix of the individuals' adjacency matrices (see for example, Table B.11 in the Appendix) of all causal combinations among the elements throughout each of the individual maps. In the next phase, we computed the distance ratios (DR_1 & DR_2) from individual maps to group maps using Equations (1) and (2), respectively. The purpose of the use of an additional measure (DR_2) was to find more evidence in favor of conclusions driven by the results of the DR_1 measure. To examine how the diversity between the group maps and the class map affected group performance, both the DR_1 and DR_2 distances were used. For the company data, first, all the board members' individual cognitive maps were aggregated to a company-level map for each company, and also individual cognitive maps in all companies were aggregated to the industry-level map. Next, the DR_1 and DR_2 distances were computed from the company's map to the industry-level map and also from the individual cognitive maps to their respective company-level ones.

Once the distance ratios were computed, we moved forward to evaluate the hypotheses. The principal of testing whether a particular hypothesis was rejected or not was based on the context of fuzzification. Fuzzification is a method of transforming exact inputs (crisp inputs) into fuzzy inputs to produce the outcomes based on the fuzzy values (Timothy, 2010, chap.4). The criteria to form the triangular fuzzy sets were based on the linguistic labels high, middle, and low and on the values of the distance ratios and performance measures. Notice that the choice of these linguistic scales was based on substantive knowledge to exhibit reasonable characteristics. Accordingly, membership degrees to the group results were calculated through the triangular membership function by putting three inputs selected as the minimum, middle, and maximum values of a given distance ratio (diversity) and performance measure. The membership degrees were also categorized into high, middle, and low, and according to the definition of the membership function, we can notate them as:

- $\mu_{low} \sim \Lambda(x; \alpha, \alpha, \beta)$,
- $\mu_{mid} \sim \Lambda(x; \alpha, \beta, \gamma)$,
- $\mu_{high} \sim \Lambda(x; \beta, \gamma, \gamma)$,

where α is the minimum of the respective values, γ is the maximum of the respective values, and $\beta = \frac{\alpha+\gamma}{2}$. We note here that the performance measure (total cumulative shareholder return values for each group of students) was taken as an external piece of information from the study and not from the cognitive maps.

We had the opportunity to collect data repeatedly in the experimental setting of the business simulation course. Since the setting was similar in all the runs of the course, we were able to pool all the observations into a single set of observations to achieve more robustness for our findings; note that the diversity and performance had to be assessed respective to each simulation run in this context to avoid unnecessary bias in the analysis. This way, we obtained the membership degrees of all observations to the respective fuzzy sets representing diversity (high-middle-low) and performance (high-middle-low). We also obtained a data set with the real-life company data for the Finnish cleantech industry. For each of the investigated rules summarized in Table B.1, we calculated the standard fuzzy F_1 consistency and coverage measures; additionally, the F_2 and F_4 measures were computed to take into account all the evidence in favor of or against the relations we investigated. In an analogous way, the fsQCA approaches were applied in the analysis of the diversity among the group and class maps to the group performance.

The first intention of the use of company data in this research was to show how the proposed method described the relation between the actual managerial cognition and company performance. Secondly, we also wanted to investigate the validity of the claims on the managerial cognition and resulting performance based on the student data sample obtained in a controlled setting of a classroom business simulation with the data from the actual managers and companies. Our analysis evaluated the hypotheses defined in Table B.1 based on the consistency and coverage measures computed from the DR_1 and DR_2 distance ratios. The analysis of the company data was done in direct analogy to the analysis of the student data. The net profit values were considered as performance measures with the company data, which were collected with other financial statistics of the selected companies. As the performance measures used for the companies were different from the performance measures used for the student data (with a direct real-life interpretation in the context of the given industry), expertly defined trapezoidal membership functions were used instead of the triangular membership functions used for the student data performance assessment. The expert definitions also allowed for the appropriate reflection of the presence of an outlier (extremely low performance of one of the companies) in the net profit data. The trapezoidal membership functions (representing high, middle, and low performance) for the net profit values were defined by the expert as: $\mu_{low} \sim \Pi(x; -100, -100, -2, -0.5)$, $\mu_{mid} \sim \Pi(x; -2, -0.5, 0.5, 2)$, and $\mu_{high} \sim \Pi(x; 0.5, 2, 100, 100)$. For DR_1 and DR_2, the triangular membership function was created in a way analogous to the student data (i.e., using α, β and γ).

To evaluate the validity of the hypotheses, we considered consistency values together with coverage values. In terms of consistency, high values were preferred, but the specific value of required consistency depended on the case we evaluated and on the consistency measure that was considered. Moreover, the evidence in favor of the hypotheses $H_{01}, \ldots, H_{09}$ was considered to be sufficient if the respective corresponding rules were significant and reasonable, in other words, if they have F_1 consistency values ranged from acceptable (approximately 0.60 and higher), through high (≥ 0.75), and to excellent (≥ 0.90). In contrast, the rules with shallow consistency values were considered not indicative of the validity of the investigated hypothesis. In the evaluation, we gave priority to consistency first and then checked the coverage scores to gain additional support for the particular condition. Literally, the coverage was a set-theoretic parameter of practical importance (used to estimate how much cause covered the effect) (Ragin, 2008). With an acceptable F_1 coverage, the reasonable cases ($0.25 \leq$ coverage ≤ 0.65) were explained as high-performance. Even though the priority was for the F_1 set-theoretic scores in the evaluation and interpretation of the results of the analysis, we considered the reasonable values of the additional F_2 measure provided a reliable confirmation of the given hypothesis. The F_4 set-theoretic measures had a different interpretation than all the other measures; values over 0.5 were indicative of more evidence than counterevidence for the rule in the given data set. We interpreted the values of the calculated consistency and coverage measures in their mutual context. As such, this paper also shows the usefulness of the recently introduced F_4 measures in practice.

All the calculations in the analysis were done using the Matlab 2018 software. In order to do the calculations, we used built-in functions in the Matlab language (e.g., forming the triangular fuzzy sets), and the rest was programmed as local functions to perform the computations and store the results. The findings of this analysis with a discussion are presented in the next section.

3. Results and discussion

As we have driven our main analysis with the data from the student sample, we first discuss those results. The advantage of the student data was the environment in which it was obtained. A business simulation in a controlled classroom setting was repeatedly performed, and the effect of interfering variables could thus be minimized. Also, the artificial company-level and industry-level maps could be easily computed. The simulation context allowed for the assumption of full information concerning the industry-level cognition (the students and their groups as stand-ins for companies were assumed to represent the full industry). A clear limitation of the use of student data is the questionable generalizability of the results. We have included students of business-oriented master's programs, who can be assumed to be taking managerial positions in companies in the future, to provide a reasonable approximation to the real-life setting. Yet, their experience is limited in certain aspects. This, however, does not limit the possibility of analysing the usefulness of the proposed methodology as well as of the performance of the recently proposed measures (DR_2, F_4 consistency and coverage) on the data. We also present and discuss the results computed for the real-life company data in comparison to the findings from the analysis of the students' data to show the relevance of the findings.

3.1. Cognitive diversity among strategic decision makers within the company

In this part, we investigate the possible links between within-company diversity and the performance of the company. The within-company diversity was operationalized as the average distance ratio (DR_1 or DR_2) of the cognitive maps of individual representatives of that company from the company-level cognitive map (the "average" of the individual cognitive maps represented by an adjacency matrix whose elements were the averages of the corresponding elements of the individual adjacency matrices).

3.1.1. Student sample

The values of the set-theoretic scores calculated for the hypothesis analysis based on DR_1 are summarized in Table B.2. It contains the overall consistency and coverage values calculated corresponding to each conditional hypothesis. $A \Rightarrow B$ denotes a conditional hypothesis established by the linguistics forms of DR_1 and group performance. Hence, the first column represents the nine hypotheses developed initially and as an example, "High, High" means if DR_1 was high, then the performance was expected to be high (the rest of them can be read in a similar way). In the table, "$Cons_{F_i}$" refers to the consistency from each measure with the i subscript of F, $i \in \{1, 2, 4\}$, and similarly, "$Cove_{F_i}$" refers to the coverage.

[Table 2 about here.]

In Table B.2, we can clearly see that only the rule of "High, High" had considerable support from the evidence, obtaining a $Cons_{F_1}(H_{09})$ of 0.5934 (that is close to the threshold) with a reasonable $Cove_{F_1}(H_{09})$ of 0.3764. The rest of the consistency measures ($Cons_{F_2} = 0.3580$ and $Cons_{F_4} = 0.5118$) also showed evidence in favor of H_{09}–namely, F_2 suggests that there was non-ambivalent "pure evidence" in favor of this hypothesis, whereas $Cons_{F_4} > 0.5$ suggests that there was more evidence for "High$\Rightarrow$ High" than there is for "High $\Rightarrow$ not-High." Even though the evidence was not very strong, the H_{09} rule and the corresponding hypothesis seemed to be supported by the student data the most when compared to the other hypotheses. There did not seem to be significant evidence of the support for the rest of the hypotheses (no other F_1 consistency is close to the required 0.6 threshold, all the values of the F_4 consistencies were below 0.5, indicating more evidence in favor of the negation of the rules instead of the rules themselves). Next, let us consider the findings based on the DR_2 measure. Table B.3 illustrates the obtained results of the consistency and coverage values concerning the DR_2 values for each hypothesis.

[Table 3 about here.]

The results in Table B.3 confirm what we observed from the DR_1 results that high diversity raised performance. However, it is apparent that the DR_2 results have produced slightly higher values of consistency and coverage than the DR_1 regarding the hypothesis of H_{09}. We can also observe that while the $Cons_{F_4}(H_{09})$ has increased with the use of DR_2, the values of $Cons_{F_4}(H_{08})$ and $Cons_{F_4}(H_{07})$ have decreased. From the construction of the F_4 measures, this suggests that under DR_2 the data support "High$\Rightarrow$ High" (i.e., H_{09}) more than any of the other hypotheses that could be summarized by "High $\Rightarrow$ not-High" (i.e. H_{08} or H_{07}). Also this support was stronger than under the DR_1 measure. By the same logic, we can conclude from the data in both tables that the case "High, Low" had the lowest consistencies, indicating that the high diversity did not seem to contribute to the low performance of the company. This was also evidenced by $Cons_{F_4}(H_{07})$ being the closest to zero and well below 0.5. If we want to investigate what performance seemed to be the most supported by the data as a result of Middle within-company diversity, then the DR_1-based results suggest that H_{06} was the most consistent with the data (H_{06} had the highest F_1 consistency of H_{06}, H_{05}, and H_{04}); however the F_4 consistency of 0.4064 meant that "Middle$\Rightarrow$not-High" had more support in the data than "Middle$\Rightarrow$High." This holds for the DR_2-based results as well, only the difference between the $Cons_{F_1}(H_{06})$ and the values of $Cons_{F_1}(H_{05})$ and $Cons_{F_1}(H_{04})$ were even smaller, suggesting there was no evidence of a rule that would specify a particular performance level based on the within-firm diversity, as long as the diversity can be described as Middle. The results for the hypotheses mapping the possible outcome of

Low diversity were analogous; only the insignificantly more supported rule seemed to be H_{03}. Based on these results, there seemed to be weak support for the H_{09} hypothesis in the data.

To make this easier to understand, the results in Table B.2 and B.3 are visualized using bar graphs in Figure B.2 and B.3, respectively. From the figures, we can see the cases where there are high consistencies and reasonable coverages to be further investigated.

[Figure 2 about here.]

[Figure 3 about here.]

Highly diverse management teams in companies might have a broader range of attitudes, skills, and abilities, which could encourage addressing challenges and making correct and reasonable strategic decisions. Undoubtedly, the companies with such enthusiastic diverse teams could be enabled to be more innovative in the operation of a business that encounters an array of volatile, complex, ambiguous, unexpected situations. As a result, such companies might earn high performance in the market. Rationally, our finding supports the idea discussed in Reynolds and Lewis (2017). However, in the research of Roberson and Jeong (2007), they showed that there can be a curvilinear U-shaped relation between diversity and company performance as a whole. In our experimental data, we found that the high diversity in top management teams influenced a high improvement of the company performance. We did not see significant evidence that low diversity led to high performance or that a middle level of diversity supported the worst performance. The reason for the lack of confirmation could be due to the partially artificial nature of the data. However, when we carefully inspect the results in Table B.2, we can see some evidence for the most consistent cause of low performance. Middle diversity might have had the highest consistencies causing low performance since we can see that $Cons_{F_1}$(Middle, Low) $>$ $Cons_{F_1}$(Low, Low) $>$ $Cons_{F_1}$(High, Low). This appears in Table B.3 as well. This is something that supports (at least weakly) to the findings of Roberson and Jeong (2007).

3.1.2. Company sample

As we did above in our analysis on the student data, we performed the same analysis on the company data. The calculated values of the consistencies and coverages are presented in Table B.4 (based on DR_1) and Table B.5 (based on DR_2). From the results in the tables, it can be seen that the case "Low⇒High" had the highest consistency, $Cons_{F_1}(H_{03}) = 0.7082$, with a reasonable coverage, $Cove_{F_1}(H_{03}) = 0.5537$, in comparison to the others. These scores clearly supported the existence of the relationship represented by H_{03}. Interestingly, as we can see in the results, the values of $Cons_{F_1}$, $Cons_{F_2}$ and $Cons_{F_4}$ were identical. This is indicative of the expert definition of the fuzzy scale used for the description of company performance being such that it resulted in crisp memberships (0 and 1) of the performances of the companies in the given membership functions. Moreover, we had acceptable consistencies of 0.6066 and with a coverage of 1 reflecting a higher empirical support of the relationship "High ⇒Middle" from the DR_1-based results. This provided clear evidence to support the relationship "High ⇒Middle" (this was also confirmed by the results based on DR_2). Also note, that even though “High ⇒High” was not unambiguously supported by the data, the statement “High⇒not-Low” has a consistency of 1 based on our data both under DR_1 and DR_2. This suggests that the High within-company diversity ruled out the Low performance.

Even though we did not find consistency scores which reached the threshold of 0.6 from the rest of evidence, the consistency values on the relation “Middle⇒Low” were again the highest from all that assumed Middle diversity as an antecedent of the rule. We can also clearly see that the support for “Middle⇒Low” was higher than for its negation, in other words, “Middle⇒not-Low” based on $Cons_{F_4}(H_{04}) > 0.5$. This suggests that there is at least some support for the validity of the hypothesis H_{04}. Furthermore, all consistencies and coverages on the relationships “High, Low”, “Middle, Middle” and “Low, Middle” were zero. This means we found no evidence from the results to support these relationships. Also, the findings with company data as student data supported the fact that $Cons_{F_1}(\text{Middle, Low}) > Cons_{F_1}(\text{Low, Low}) > Cons_{F_1}(\text{High, Low})$ suggesting that the middle diversity had the strongest association with Low company performance based on the data. Generally, the evidence from the analysis of the company data seemed to support the findings of Roberson and Jeong (2007).

[Table 4 about here.]

[Table 5 about here.]

3.2. Cognitive diversity between the companies within an industry

3.2.1. Student sample

So far, we have discussed how the decision-makers within companies and the diversity of their cognitive frames affected the company performance across the results obtained over the analyses using the student and company data samples. We could have also abstracted from the individual level, considered companies to be the smallest analyzed units, and asked how the diversity within the industry (i.e., the differences of the strategic frames of the companies from the industry-level strategic frame) affected the performance of the companies. This was also possible with both our samples, as we could have easily used company-level cognitive maps (these were already available from the previous analysis) and their average as the industry-level cognitive map. The purpose of this analysis was to understand the impacts of the strategy frame of a company and its difference from the industry-level strategy frame on the performance of the company. We operationalized the company-industry cognitive diversity by the distance ratios (DR_1 and DR_2) of the company-level cognitive maps (an average cognitive map of all the students that represented the same company in the simulation task) from the industry-level one. We were again interested in the same set of possible relationships between such an understanding of cognitive diversity and company performance as summarized in Table B.1. Note that the difference from the previous analysis lies in the shift of the meaning of cognitive diversity; previously, the within-company diversity was considered, whereas we were now focusing on the diversity of companies within the given industry. Using the distance ratios DR_1 and DR_2, we have calculated the set-theoretic F_1, F_2, and F_4 consistency and coverage measures. The results which are based on DR_1 and DR_2 are shown in Table B.6 and B.7, respectively.

[Table 6 about here.]

[Table 7 about here.]

According to the results (shown in Table B.6 and B.7), we can see that the student data did not offer many strong insights into the possible relationship of the difference of the strategic frames of the companies and the industry-level strategic frame with the performance of the companies. Under DR_1, the hypothesis most consistent with the data was H_{06}, based on its $Cons_{F_1}(H_{06}) = 0.5722$ and the same held under DR_2, in this case, $Cons_{F_1}(H_{06}) = 0.6027$. Even though this relationship seemed to pass the required consistency threshold for DR_2, the evidence in its favor could hardly be considered strong, as the support for "Middle⇒High" was almost as strong in the data as the support for the negation of this relationship, in other words, for "Middle⇒not-High". A similar case was observed for H_{09} in the previous analysis (where within-company diversity was considered). The performance of the company seemed to be rather unpredictable based on the cognitive diversity, as long as the diversity was high. As for the anticipated outcome of the Low cognitive diversity, the relationship "Low⇒not-Low" seemed to have some support in the student data (note the rather low consistencies of H_{01}). Apart from these findings, the results on the student data seemed to be rather inconclusive. The inconclusiveness of the results on student data might be due to the already mentioned low experience of the student participants. This might have influenced the industry-level strategy frame represented by the collective cognitive map. In real-life data based on the much higher experience of the actual managers, the industry-level map might be different, and the cognitive diversity measured by the distance of the company's cognitive map from the industry-level one might then stress different aspects. While the interpretations of the results of the analysis and the example of the application of the proposed analytical methodology remain valid, we do not propose any practical implications of the student-based analysis in the context of within-industry diversity and its effect on company performance, due to the limits of the student sample and the limited ability to derive a meaningful industry-level cognitive frame from it. This should, however, not be an issue in real-life data obtained from companies, however we do have a representative sample of an industry at our disposal.

3.2.2. Company sample

We have investigated the same hypotheses concerning the effect of within-industry diversity and performance using the company data. The calculated values of the F_1, F_2, and F_4 set-theoretic consistency and coverage measures are shown in Table B.8 based on DR_1 and Table B.9 based on DR_2.

[Table 8 about here.]

[Table 9 about here.]

As can be seen from Table B.8, both $Cons_{F_1}(H_{03})$ and $Cons_{F_1}(H_{09}) > 0.73$ over the DR_1-based results. The results for H_{03} and H_{09} are even stronger with the DR_2. Also, the DR_1-based $Cove_{F_1}(H_{03}) = 0.3122$ and $Cove_{F_1}(H_{09}) = 0.5415$ provide reasonable empirical support in favor of each of these relationships. From the perspective of F_4 measures, we can also see that the evidence in favor of the validity of H_{03} and H_{09} was much stronger than the evidence against these hypotheses. This can be interpreted as strong evidence which supported the existence of the relations "Low⇒High" and "High⇒High."

Furthermore, we also had F_1 consistency (0.6212 based on DR_1 and 0.6768 based on DR_2) and coverage (0.6667 based on DR_1 and 0.6768 based on DR_2) on the relation "Middle⇒Low." This suggests that the middle diversity between companies within an industry was associated with low performance of the company (H_{04}). These findings are in agreement with what was weakly suggested by the student data in the within-company diversity context and what was clearly found in the company data in the same context. Overall, the presented results seem to be in line with Roberson and Jeong (2007), in other words, we have confirmed the possibility of existence of a curvilinear U-shaped relationship between cognitive diversity and company performance. This was now primarily supported by hypotheses H_{03}, H_{09} (high performance in case of high diversity and low diversity), and also by H_{04} (which was indicating low performance for middle diversity). We thus extend the findings of Roberson and Jeong (2007), since our analysis was focused on differently defined cognitive diversity–mainly on the within-company and within-industry cognitive diversity.

4. Conclusion

Theoretically, our findings contribute to the literature of strategic cognition by providing empirical evidence of the existence of a relationship between cognitive diversity and company performance. Regarding cognitive diversity among strategic decision-makers, our findings supported the findings of Roberson and Jeong (2007). It seems that more cognitive diversity within a decision-making team can lead to better levels of the performance. However high cognitive diversity might not be the only way towards high performance; low cognitive diversity seems to give strong grounds for high performance as well, and middle diversity can indicate lower performance. The reasons behind this can come from several possible sources (e.g., from competitive intensity and technological turbulence) and may moderate such relationships. Regarding cognitive diversity between companies in a market, we found support for the U-shaped relationship between cognitive diversity and company performance. This means that the companies with very different perceptions of the causalities leading to high performance compared to the dominant logic of the market are likely to perform well. They either find their market niche or are able to disrupt the market with their unique strategy. On the other hand, the companies that are cognitively at the core of the market's dominant logic also reach high levels of performance. The companies with a middle level of distance from the market's dominant logic are the most likely to perform poorly. We also found this with the company data as our H_{04} hypothesis ("Middle $\Rightarrow$ Low") was supported.

Methodologically, we contribute to the study of managerial cognition by demonstrating how relationships regarding managerial cognitive diversity (within and between companies) can be empirically assessed even with small sample sizes. The proposed method enables the examination of the relationship between managerial-level cognition and company performance and then suggests what could be understood of the impact of diversity to achieve better performance during operations in the market. This approach supports managers and organizations in gaining insight into management team operations and how they affect performance within market change. Notably, this proposed method has the potential to study how diversity through individuals' thoughts, abilities, and skills are meaningful to changes in the industry. The method is based on using fuzzy set-theory, concepts in fsQCA, and distance ratio measures, thus, it can be an efficient tool for producing precise measures to make decisions at first sight.

While introducing a novel methodology, this research aimed to explore the relation between managerial-level cognition and industry-level performance through shared cognitive maps produced by students in a strategic decision-making process in a controlled setting of a business simulation. In addition to that, we introduced nine hypotheses based on the diversity (high-middle-low) and performance (high-middle-low) to be tested under two different definitions of cognitive diversity, within-company and within-industry. To do so, a total of 431 cognitive maps were created for this study. The maps were produced by the teams of graduate students in outlining their beliefs, views, and decisions in a strategic issues operation. In the analytical phase, we deployed two distance ratio measures and innovative techniques in fsQCA.

In the analysis, we first investigated how the cognitive diversity between strategic decision-makers within a company affected company performance. From the empirical evidence obtained, the first results with the student sample suggested that there might be an impact of high-level cognitive diversity on the enhancement of the performance of the company in a market. We also tested our method with real company data in which the cognitive maps were produced by managers in nine selected companies in Finland. From the results in the analysis of these shared cognitive maps, it was confirmed with sufficient evidence that low cognitive diversities of the experts led to high company performance. The findings from both results corroborated what was revealed by Roberson and Jeong (2007). Next, we did an analysis to study the relation of the diversity between companies within an industry to company performance. In this investigation, even though the results for the student data were inconclusive, possibly due to the limitations of the sample, we managed to find conclusive results for the real-life company data. We managed to found evidence in favor of the curvilinear U-shaped relation (Roberson and Jeong, 2007) of the diversity between companies within an industry with company performance.

Despite its exploratory nature, this study has offered some insight into our understanding of the novel distance ratio measure (DR_2) by Bergman et al. (2020) and set-theoretic scores (F_2 and F_4) by Stoklasa et al. (2017, 2018). As far as we know, this is the first time that the distance ratios together with the fsQCA have been used to explore the knowledge from the strategic cognitive frames. In doing so, we demonstrated that the distance ratio measures with the fsQCA approaches are powerful techniques for analysing cognitive maps and cognitive diversity in the maps.

A number of possible future studies using the proposed approach are apparent. For example, it would be interesting to assess the effects of cognition and the decisions of persons who are at the top level in the organization as they dominate an organization's cognitive operations. In addition, market influences, institutional affiliations of directors, tourism policies, processes in manufacturing systems, and so on can be conceptualized in cognitive frames and then could drive examinations to produce useful information. All in all, we are confident that the method introduced can be used for future studies on the current topics related to cognitive mapping and the evaluation of cognitive maps in a wide range of real-world applications.

Appendix A.

[Table 10 about here.]

Appendix B.

[Table 11 about here.]

References

Axelrod, R., 1976. Structure of decisions: the cognitive maps of political elites. Princeton University Press.

Baumgartner, M., Thiem, A., 2017. Model ambiguities in configurational comparative research. Sociological Methods & Research 46, 954–987. doi:10.1177/0049124115610351.

Bergman, J.P., Knutas, A., Luukka, P., Jantunen, A., Tarkianen, A., Karlik, A., Platonov, V., 2016. Strategic interpretation on sustainability issues-eliciting cognitive maps of boards of directors. Corporate Governance 16, 162–186.

Bergman, J.P., Luukka, P., Jantunen, A., Tarkianen, A., 2020. Cognitive diversity, managerial characteristics and performance development among the cleantech. International Journal of Knowledge-Based Organizations 10. doi:10.4018/IJKBO.2020010101.

Bezdek, J., 1981. Pattern recognition with fuzzy objective function algorithms. Plenum Press, New York.

Bittner, E.A.C., Leimeister, J.M., 2014. Creating shared understanding in heterogeneous work groups: Why it matters and how to achieve it. Journal of Management Information Systems 31, 111–143.

Bondy, J.A., Murty, U.S.R., 1976. Graph theory with applications. Elsevier.

Braumoeller, B.F., 2017. Aggregation bias and the analysis of necessary and sufficient conditions in fsqca. Sociological Methods & Research 46, 242–251. doi:10.1177/0049124116672701.

Carvalho, J.P., Tome, J.A.B., 2000. Fuzzy Mechanisms for Qualitative Causal Relations. Springer Berlin Heidelberg, Berlin, Heidelberg.

Clarkson, G.P., Hodgkinson, G.P., 2005. Introducing cognizer^{TM}: A comprehensive computer package for the elicitation and analysis of cause maps. Organizational Research Methods 8, 326–349. doi:10.1177/1094428105278022.

Downs, R.M., Stea, D., 1973. Cognitive maps and spatial behavior: Process and products. Image and Environment , 8–26doi:10.1002/9780470979587.ch41.

Dubois, D., Prade, H., 1980. Fuzzy sets and systems: Theory and applications. Academic Press.

Elliot, T., 2013. Fuzzy-set/qualitative comparative analysis 2.0. Tucson, Arizona: Department of Sociology, University.

Evans, J.R., 2005. Total quality management, organization, and strategy, 4th ed. Mason, OH: Thomson South-Western.

Ferreira, F.A.F., Jalali, M.S., Ferreira, J.J.M., 2016. Experience-focused thinking and cognitive mapping in ethical banking practices: From practical intuition to theory. Journal of Business Research 69, 4953–4958.

Ferreira, F.A.F., Marques, C.S.E., Bento, P., Ferreira, J.J.M., Jalali, M.S., 2015. Operationalizing and measuring individual entrepreneurial orientation using cognitive mapping and mcda techniques. Journal of Business Research 68, 2691–2702.

Gabriel, A.S., Campbell, J.T., Djurdjevic, E., Johnson, R.E., Rosen, C.C., 2018. Fuzzy Profiles: Comparing and Contrasting Latent Profile Analysis and Fuzzy Set Qualitative Comparative Analysis for Person-Centered Research. Organizational Research Methods 21, 877–904. doi:10.1177/1094428117752466.

Gary, M.S., Wood, R.E., 2011. Mental models, decision rules, and performance heterogeneity. Strategic Management Journal 32, 569–594.

Gerard, P., John, A., Nicola, J., 2004. Causal cognitive mapping in the organizational strategy field : A comparison of alternative elicitation procedures. Organizational Research Methods 7, 3–26. doi:10.1177/1094428103259556.

Greckhamer, T., V.F., M., Elms, H., Lacey, R., 2007. Using qualitative comparative analysis in strategic management research: An examination of combinations of industry, corporate, and business-unit effects. Organizational Research Methods 114, 695–726.

Haumann, T., Gunturkun, P., Schons, L.M., Wieseke, J., 2015. Engaging customers in coproduction processes: How value-enhancing and intensity-reducing communication strategies mitigate the negative effects of coproduction intensity. Journal of Marketing 79, 17–33. doi:10.1509/jm.14.0357.

Jenkins, M., Johnson, G., 1997. Linking managerial cognition and organizational performance: A preliminary investigation using causal maps. British Journal of Management 8, S77–S90. doi:10.1111/1467-8551.8.s1.7.

Kane, H., Lewis, M.A., Williams, P.A., Kahwati, L.C., 2014. Using qualitative comparative analysis to understand and quantify translation and implementation. Translational Behavioral Medicine 4, 201–208.

Kaplan, R.S., Norton, D.P., 2004. How strategy maps frame an organization's objectives. Financial Executive. 20, 40–45.

Kaplan, S., 2011. Research in cognition and strategy: Reflections on two decades of progress and a look to the future. Journal of Management Studies 48, 665–695.

Kichin, R.M., 1994. Psychology. Journal of Environmental Psychology , 1–19.

Klir, G.J., Yuan, B., 1995. Fuzzy Sets and Fuzzy Logic: Theory and Applications. doi:10.1109/9780470544341.ch11.

Langfield-Smith, K., Wirth, A., 1992. Measuring differences between cognitive maps. Journal of the Operational Research Society 43, 1135–1150.

Mamdani, E., Assilian, S., 1975. An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man Machine and System 7, 1–13. doi:10.1016/S0020-7373(75)80002-2.

Marcel, J.J., Barr, P.S., Duhaime, I.M., 2011. The influence of executive cognition on competitive dynamics. Strategic Management 32, 115–138.

Markoczy, L., Goldberg, J., 1995. A method for eliciting and comparing causal maps. Journel of Management 21, 305–333. doi:10.1177/014920639502100207.

Marshall, R., 2013. Guest editorial: Cognitive mapping of strategy in marketing. Journal of Business Research 1541–1543, 1541–1543.

Meuer, J., Rupietta, C., 2016. Integrating qca and hlm for multilevel research on organizational configurations. Organizational Research Methods 20, 324–342.

Mikkelsen, K.S., 2017. Fuzzy-set case studies. Sociological Methods & Research 46, 422–455. doi:10.1177/0049124115578032.

Narayanan, V.K., Zane, L.J., Kemmerer, B., 2011. The cognitive perspective in strategy: An integrative review. Journal of Management 37, 305–351. doi:10.1177/0149206310383986.

Nelson, K.M., Nadkarni, S., Narayanan, V.K., Ghods, M., 2000. Understanding software operations support expertise: A revealed causal mapping approach. MIS Quarterly 24, 475–507. doi:10.2307/3250971.

Ragin, C.C., 1987. The Comparative Method. Berkeley: University of California.

Ragin, C.C., 2000. Fuzzy-set social science. chicago: University of chicago press.

Ragin, C.C., 2006. Set relations in social research: Evaluating their consistency and coverage. Political Analysis 14, 291–310. doi:10.1093/pan/mpj019.

Ragin, C.C., 2008. Redesigning social inquiry: Fuzzy sets and beyond.

Ragin, C.C., 2014. The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies. University of California, Oakland.

Reynolds, A., Lewis, D., 2017. Teams Solve Problems Faster When They're More Cognitively Diverse. Harvard Business Review.

Roberson, Q.M., Jeong, H., 2007. Examining the link between diversity and firm performance: The effects of diversity reputation and leader racial diversity. Group & Organization Management 32, 548–568. doi:10.1177/1059601106291124.

Roig-Tierno, N., Huarng, K.H., Ribeiro-Soriano, D.E., 2016. Set-theoretic research in business. Journal of Business Research 69.

Santos, J.N., Mota, J., Baptista, C.L., 2018. Understanding configurations of value creation functions in business relationships using a fuzzy-set qca. Journal of Business Research 89, 429–434.

Scavarda, A.J., Chameeva, T.B., Goldstein, S.M., Hays, J.M., Hill, A.V., 2006. A methodology for constructing collective causal maps. Decision Sciences 37, 263–283. doi:10.1111/j.1540-5915.2006.00124.x.

Schneider, C., Wagemann, C., 2012. Set-Theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis. Cambridge, UK: Cambridge University Press.

Schneider, C.Q., Rohlfing, I., 2016. Case studies nested in fuzzy-set qca on sufficiency: Formalizing case selection and causal inference. Sociological Methods & Research 45, 526–568.

Skaaning, S.E., 2011. Assessing the robustness of crisp-set and fuzzy-set qca results. Sociological Methods & Research 40, 391–408. doi:10.1177/0049124111404818.

Skarmeas, D., Leonidou, C.N., Saridakis, C., 2014. Examining the role of csr skepticism using fuzzy-set qualitative comparative analysis. Journal of Business Research 67, 1796–1805.

Stoklasa, J., Luukka, P., Talášek, T., 2017. Set-theoretic methodology using fuzzy sets in rule extraction and validation - consistency and coverage revisited. Information Sciences 412-413, 154–173.

Stoklasa, J., Talášek, T., Luukka, P., 2018. On consistency and coverage measures in the fuzzified set-theoretic approach for social sciences: dealing with ambivalent evidence in the data. in Proc. of the 36th Inter. Conf. on Mathematical Methods in Economics , 521–526.

Sugeno, M., Kang, G., 1988. Structure identification of fuzzy model. Fuzzy Sets and Systems 28, 15–33.

Takagi, T., Sugeno, M., 1985. Fuzzy identification of systems and its applications to modeling and control. IEEE Trans. Syst., Man, Cybern 15, 116–132. doi:10.1109/TSMC.1985.6313399.

Tierno, N.R., Cruz, T.F.G., Martinez, J.L., 2017. An overview of qualitative comparative analysis: A bibliometric analysis. Journal of Innovation and Knowledge 2, 15–23.

Timothy, J.R., 2010. Fuzzy Logic with Engineering Applications: Third Edition.

Vis, B., Dul, J., 2018. Analyzing relationships of necessity not just in kind but also in degree: Complementing fsqca with nca. Sociological Methods & Research 47, 872–899. doi:10.1177/0049124115626179.

Wang, X.H., Kim, T.Y., Lee, D.R., 2016. Cognitive diversity and team creativity: Effects of team intrinsic motivation and transformational leadership. Journal of Business Research 69, 3231–3239.

Zadeh, L.A., 1965. Fuzzy sets. Information and Control 8, 338–353.

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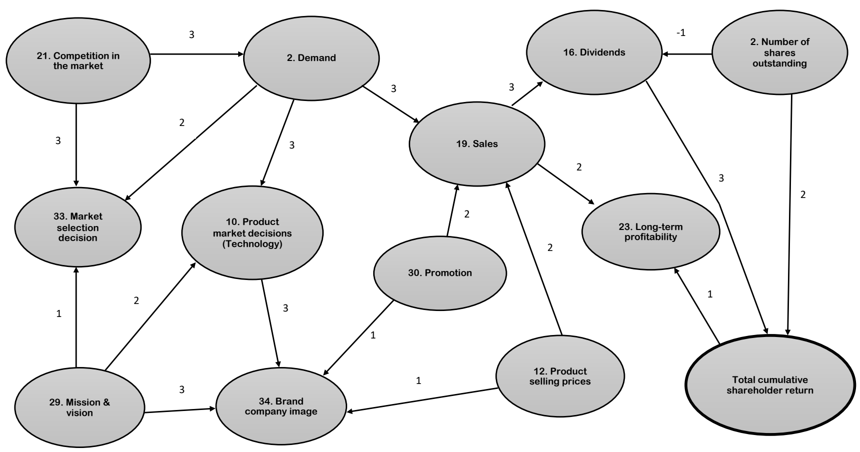

Figure B.1: An example of a cognitive map in the original data of the study, as provided by the students in the business simulation task.

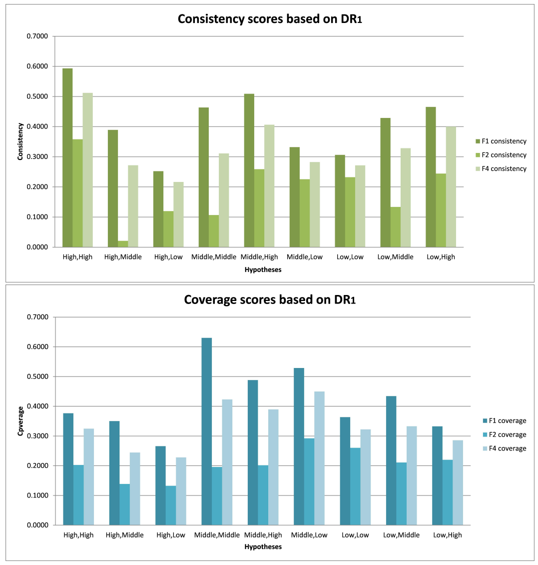

Figure B.2: Results of consistency and coverage values based on DR_1 in the evaluation of the hypotheses.

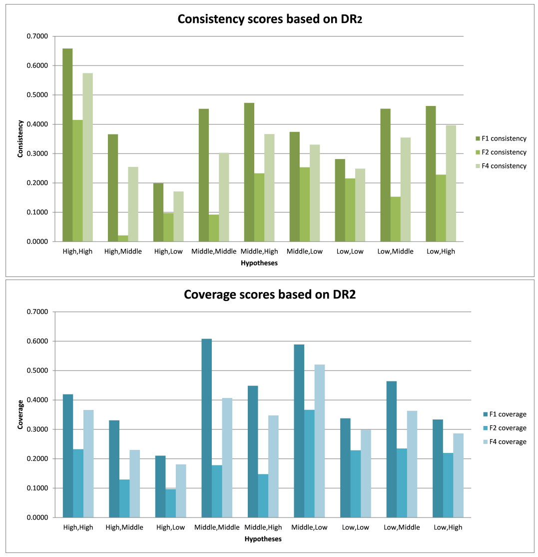

Figure B.3: Results of consistency and coverage values based on DR_2 in the evaluation of the hypotheses.

List of Tables

Table B.1: The hypothesis models in linguistic levels with distance ratios and group performance.

		Group Performance		
		low	middle	high
	low	H_{01}	H_{02}	H_{03}
DR	middle	H_{04}	H_{05}	H_{06}
	high	H_{07}	H_{08}	H_{09}

Table B.2: The results of the consistencies and coverages obtained over the DR_1 for all the hypotheses with the student data, when the within-company diversity was considered.

	DR_1 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) **High, High**	**0.5934**	**0.3764**	**0.3580**	**0.2026**	**0.5118**	**0.3247**
(H_{08}) High, Middle	0.3891	0.3499	0.0211	0.1387	0.2716	0.2443
(H_{07}) High, Low	0.2522	0.2659	0.1197	0.1325	0.2164	0.2281
(H_{05}) Middle, Middle	0.4635	0.6300	0.1065	0.1956	0.3112	0.4229
(H_{06}) Middle, High	0.5091	0.4879	0.2587	0.2016	0.4064	0.3895
(H_{04}) Middle, Low	0.3320	0.5288	0.2254	0.2921	0.2823	0.4496
(H_{01}) Low, Low	0.3063	0.3635	0.2321	0.2602	0.2714	0.3221
(H_{02}) Low, Middle	0.4286	0.4341	0.1335	0.2109	0.3285	0.3326
(H_{03}) Low, High	0.4653	0.3323	0.2443	0.2198	0.3999	0.2856

Table B.3: The results of the consistencies and coverages obtained over the DR_2 for all the hypotheses with the student data, when the within-company diversity was considered.

	DR_2 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) **High, High**	**0.6582**	**0.4195**	**0.4147**	**0.2326**	**0.5744**	**0.3661**
(H_{08}) High, Middle	0.3660	0.3308	0.0211	0.1293	0.2546	0.2300
(H_{07}) High, Low	0.1987	0.2104	0.0972	0.0967	0.1710	0.1811
(H_{05}) Middle, Middle	0.4526	0.6082	0.0919	0.1782	0.3028	0.4068
(H_{06}) Middle, High	0.4730	0.4483	0.2328	0.1476	0.3667	0.3475
(H_{04}) Middle, Low	0.3741	0.5890	0.2536	0.3666	0.3305	0.5205
(H_{01}) Low, Low	0.2814	0.3377	0.2155	0.2289	0.2487	0.2984
(H_{02}) Low, Middle	0.4530	0.4638	0.1529	0.2352	0.3547	0.3631
(H_{03}) Low, High	0.4622	0.3338	0.2281	0.2200	0.3966	0.2864

Table B.4: The results of the consistencies and coverages obtained over the DR_1 for all the hypotheses for the company data.

	DR_1 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) High, High	0.3934	0.1297	0.3934	0.0000	0.3934	0.1297
(H_{08}) **High, Middle**	**0.6066**	**1.0000**	**0.6066**	**1.0000**	**0.6066**	**1.0000**
(H_{07}) High, Low	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{05}) Middle, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{06}) Middle, High	0.4599	0.3166	0.4599	0.1406	0.4599	0.3166
(H_{04}) Middle, Low	0.5401	0.6198	0.5401	0.2808	0.5401	0.6198
(H_{01}) Low, Low	0.2918	0.3802	0.2918	0.0411	0.2918	0.3802
(H_{02}) Low, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{03}) **Low, High**	**0.7082**	**0.5537**	**0.7082**	**0.5073**	**0.7082**	**0.5537**

Table B.5: The results of the consistencies and coverages obtained over the DR_2 for all the hypotheses for the company data.

	DR_2 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) High, High	0.4439	0.1597	0.4439	0.0000	0.4439	0.1597
(H_{08}) High, Middle	0.5561	1.0000	0.5561	1.0000	0.5561	1.0000
(H_{07}) High, Low	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{05}) Middle, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{06}) Middle, High	0.4372	0.2887	0.4372	0.0807	0.4372	0.2887
(H_{04}) Middle, Low	0.5628	0.6195	0.5628	0.3334	0.5628	0.6195
(H_{01}) Low, Low	0.2928	0.3805	0.2928	0.0945	0.2928	0.3805
(H_{02}) Low, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{03}) **Low, High**	**0.7072**	**0.5516**	**0.7072**	**0.5032**	**0.7072**	**0.5516**

Table B.6: The results of the consistencies and coverages obtained over the DR_1 for all the hypotheses for the student data, with diversity operationalized by the distance ratio of the company-level cognitive map and the industry-level one.

	DR_1 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) High, High	0.4056	0.2963	0.2292	0.1790	0.3631	0.2653
(H_{08}) High, Middle	0.3620	0.3749	0.0817	0.1952	0.2859	0.2961
(H_{07}) High, Low	0.3846	0.4668	0.2807	0.2417	0.3510	0.4260
(H_{05}) Middle, Middle	0.3692	0.5378	0.0882	0.2341	0.2777	0.4045
(H_{06}) Middle, High	0.5722	0.5879	0.3674	0.3716	0.5107	0.5247
(H_{04}) Middle, Low	0.2416	0.4124	0.1654	0.1392	0.2116	0.3613
(H_{01}) Low, Low	0.2444	0.2230	0.1509	0.1749	0.2331	0.2127
(H_{02}) Low, Middle	0.4544	0.3539	0.1105	0.2299	0.3845	0.2994
(H_{03}) Low, High	0.4411	0.2423	0.1907	0.1432	0.3825	0.2101

Table B.7: The results of the consistencies and coverages obtained over the DR_2 for all the hypotheses for the student data, with diversity operationalized by the distance ratio of the company-level cognitive map and the industry-level one.

	DR_2 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) High, High	0.3999	0.3211	0.2006	0.1642	0.3450	0.2771
(H_{08}) High, Middle	0.3961	0.4511	0.0912	0.2317	0.3095	0.3524
(H_{07}) High, Low	0.3774	0.5036	0.2716	0.2872	0.3455	0.4611
(H_{05}) Middle, Middle	0.3526	0.4824	0.0775	0.1787	0.2496	0.3416
(H_{06}) **Middle, High**	**0.6027**	**0.5816**	**0.4014**	**0.3422**	**0.5323**	**0.5137**
(H_{04}) Middle, Low	0.2506	0.4018	0.1768	0.1090	0.2180	0.3496
(H_{01}) Low, Low	0.2222	0.1990	0.1283	0.1226	0.2114	0.1893
(H_{02}) Low, Middle	0.4556	0.3482	0.1168	0.2639	0.4005	0.3060
(H_{03}) Low, High	0.4325	0.2331	0.1876	0.1507	0.3882	0.2092

Table B.8: The results of the consistencies and coverages obtained over the DR_1 for all the hypotheses for the company data, with diversity operationalized by the distance ratio of the company-level cognitive map and the industry-level one.

	DR_2 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) **High, High**	**0.7303**	**0.5415**	**0.7303**	**0.4829**	**0.7303**	**0.5415**
(H_{08}) High, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{07}) High, Low	0.2697	0.3333	0.2697	0.1707	0.2697	0.3333
(H_{05}) Middle, Middle	0.1515	0.4878	0.1515	0.0000	0.1515	0.4878
(H_{06}) Middle, High	0.2273	0.1463	0.2273	0.0000	0.2273	0.1463
(H_{04}) **Middle, Low**	**0.6212**	**0.6667**	**0.6212**	**0.5041**	**0.6212**	**0.6667**
(H_{01}) Low, Low	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{02}) Low, Middle	0.2471	0.5122	0.2471	0.0244	0.2471	0.5122
(H_{03}) **Low, High**	**0.7529**	**0.3122**	**0.7529**	**0.2244**	**0.7529**	**0.3122**

Table B.9: The results of the consistencies and coverages obtained over the DR_2 for all the hypotheses for the company data, with diversity operationalized by the distance ratio of the company-level cognitive map and the industry-level one.

	DR_2 based consistency and coverage values					
$A \Rightarrow B$	$Cons_{F_1}$	$Cove_{F_1}$	$Cons_{F_2}$	$Cove_{F_2}$	$Cons_{F_4}$	$Cove_{F_4}$
(H_{09}) **High, High**	**0.7460**	**0.5697**	**0.7460**	**0.5394**	**0.7460**	**0.5697**
(H_{08}) High, Middle	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{07}) High, Low	0.2540	0.3232	0.2540	0.1919	0.2540	0.3232
(H_{05}) Middle, Middle	0.1616	0.4848	0.1616	0.0000	0.1616	0.4848
(H_{06}) Middle, High	0.1616	0.0970	0.1616	0.0000	0.1616	0.0970
(H_{04}) **Middle, Low**	**0.6768**	**0.6768**	**0.6768**	**0.5455**	**0.6768**	**0.6768**
(H_{01}) Low, Low	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(H_{02}) Low, Middle	0.2361	0.5152	0.2361	0.0303	0.2361	0.5152
(H_{03}) **Low, High**	**0.7639**	**0.3333**	**0.7639**	**0.2667**	**0.7639**	**0.3333**

Table B.10: Pool of strategic topics on sustainable return to shareholders.

ID	Company's strategic issues	ID	Company's strategic issues
1	Market share	21	Competition in the market
2	Demand	22	Short-term profitability
3	Own manufacturing	23	Long-term profitability
4	Contract manufacturing	24	Growth of the company
5	Inventory management	25	Employee training and education
6	Investment in production and plants	26	Consumer price elasticity
7	Number of R&D personnel	27	R&D employee turnover
8	In-house R&D	28	Wages of R&D employees
9	Buying technology and design licenses	29	Mission and vision
10	Product-market decisions (technology)	30	Promotion
11	Feature offered	31	Transportation cost
12	Product selling prices	32	Interest rates
13	Logistics priorities	33	Market selection decisions
14	Transfer prices	34	Brand, company image
15	Long-term debt	35	Capacity allocation
16	Dividends	36	Network coverage
17	Number of shares outstanding	37	Equity ratio
18	Internet loans	38	Environmental sustainability
19	Sales	39	Supplier selection
20	Corporate tax rate	40	Supply chain ethics

Table B.11: An example of a 41×41 adjacency matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	.	.	.	36	37	38	39	40	41
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	3
2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	2
3	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
8	0	0	2	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	1
11	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	.	.	.	0	-2	0	0	0	-1
16	0	0	0	0	0	0	0	-2	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	3
17	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	-1	0	0	.	.	.	0	0	0	0	0	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
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36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	1	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	-1	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.	0	0	0	0	0	0