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An investigation of hidden shared linkages among perceived causal relationships in cognitive maps

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Abstract This study investigates cause and effect relationships in cognitive maps and the coexistence of pairs of such relationships in cognitive maps of a chosen group of decision-makers. We call the existence of a pair of causal relationships shared by the group of decision-makers in their cognitive maps *inter-causal relationship*. We investigate the coexistence of the chosen pairs of causal relationships in the maps in terms of one of the causal relationships being a necessary and/or sufficient condition for the existence of the other using the tools of fuzzy-set qualitative comparative analysis. We develop and propose a framework to extract and examine the inter-causal relationships from the cognitive maps. The proposed method is based on set-theoretic consistency and coverage measures. We used empirical data (of 71 cognitive maps) collected from a cognitive mapping approach performed by individuals in management teams within a strategic decision-making simulation process to test the proposed approach. Empirical results show that our method can identify inter-causal relationships and provide analytic results for a more complex interpretation if the information arises from the structure of cognitive maps.
Keywords: Cognitive map, Consistency, Coverage, Decision-making, Inter-causal relationship.

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1 Introduction

There is no doubt that individual perceptions play a vital role in creating, evaluating, and choosing the decision options in the decision-making process [22]. It is common knowledge that individual perceptions are primarily derived from personal experience and knowledge. The perceptions might also be influenced by other factors, such as beliefs, interests, and expectations [22]. This means that rationales behind the problems/situations are perceived in various ways, and they might differ from one person to another. To understand this phenomenon and make efficient analyses, there has been a growing interest in using cognitive mapping as a participatory method [10]. A cognitive map as a cause-effect network of qualitative aspects [29] helps individuals represent their thinking about a problem or situation. Cognitive maps have been of continuing interest in many applications in social science including strategic management and business research [3, 4, 12], engineering and technology [16], industrial and manufacturing [27, 20, 14, 5], medicine[19, 8, 30, 18], politics [1] and environmental research [17, 28].

Shared cognitive maps or shared linkages therein refer to shared mental representation of a problem or situation with concepts of a team across gathering, sharing, and jointly analyzing and integrating [3]. The word "shared" might have two different meanings, either dividing things up or having things in common [15]. In the strategic management studies, both meanings of the word "shared" are suitable in terms of the cognitive representations because–on some occasions, responsibilities and expertise are divided between team members, and some other times they take the tasks in common. That is important to mention here because this study uses data of cognitive maps that were created by individuals in strategic management teams, but looks for structures therein that are shared by the whole team or that can be considered to constitute the shared understanding (cognition) of the system/concept represented by the causal maps. We are particularly interested in the ability to infer the existence of one causal relationship in the map from the existence of another one.

The relationship between two events/cases (elements in the cognitive map) such that one causes the other is defined as causality. In cognitive science, causality is a critical aspect that plays a vital role in decision-making and often supports choosing a course of action that seems best to achieve the expected outcomes [6]. In the cognitive maps, causal phenomena are revealed as cause-and-effect relationships between concepts, and according to those relationships, the topology and workflow of the effects are designed [2]. The cognitive maps are representations of individuals' perceived causal structures (i.e. network of causal relationships) in a given context. Networked nature of perceived causalities implies that specific cause-and-effect relationships are interrelated (e.g. they either have a causal connection between them, or the existence of one might imply the existence of the other in the causal map and the cognitive structure it represents), even though these linkages are not directly marked into cognitive map. We define the relationships of coexistence of two causal relationships in the cognitive maps of the members of a chosen group as inter-causal relationships. Even more specifically, if we assume four concepts A, B, C, and D in a cognitive map, then the inter-causal relationship between a causal relationship $A \rightarrow B$ and a causal relationship $C \rightarrow D$ is defined as the presence of $A \rightarrow B$ implying the presence of $C \rightarrow D$ in the shared cognitive structure.

Examining the cognitive maps implies assessing the causal relationships to extract valuable information for future operations in a particular area. In this study, we attempt to investigate the hidden shared relationship of coexistence between two causal relationships in a group cognitive structure (i.e., across the cognitive maps of the members of the analysed group) - the *inter-causal relationships*. To the best of our knowledge, there is no previous research that explores such a linkage between two perceived causal relationships-this makes our study novel in this regard. In the practical example of the use of our method we limit ourselves to the role of individual perceived causalities presented in the cognitive maps regarding a strategic decision-making process and their inter-causal relationships. To investigate this, we develop and present a methodology based on set-theoretic consistency and coverage measures. We used empirical data collected from a cognitive mapping approach performed by the individuals in management teams within a strategic decision-making process simulation. The simulation was run as a part of a graduate course in business at LUT University, Lappeenranta, Finland.

The rest of this chapter is organized as follows: Section 2 presents a description of the used data, key theoretical aspects applied, and the methodology. Section 3 presents and discusses observed results. Section 4 summarizes the main findings and presents concluding remarks.

2 Data, theoretical aspects and methodology

2.1 Data sample

To investigate the relation between perceived causal relationships, we analyze a data sample of cognitive maps collected from an eight-week business simulation task in a controlled setting that was performed with graduate students of a business-oriented program. During the simulation task, the students were guided to understand and interpret the operations of international trading strategies in global business in a dynamic and competitive environment. This simulation resulted in a collection of cognitive maps that were shaped by the individuals. In the data sample, there were 71 individual-level cognitive maps originally belonging to 16 management teams in the simulation, but the grouping is not relevant for the purposes of this study) created based on the 40 strategic-level constructs presented in Table D.1 in the Appendix. From this list, each individual selected 12 constructs seen as the most relevant from his/her knowledge and unique views on the situation to create his/her cognitive map. Each cognitive map also included the total cumulative shareholder returns (TCSR), as the causation of TCSR was the main point of investigation in the course/simulation. To carry out the necessary analysis and calculations with the cognitive maps, all individual cognitive maps were converted into association matrices. The 40 strategic-level constructs plus the TCSR defined each dimension of the matrix (i.e., 41×41 association matrix was used to represent an individual map). Each cell value of the matrix represents the strength of the causal relationship between two elements in the cognitive maps; these strengths were chosen from the $\{-3, -2, -1, 1, 2, 3\}$ set. This allowed for all the cognitive maps to be represented by a 41×41 association matrix; the rows/columns that corresponded with strategic concepts that were not used in the cognitive map of the given individual consisted entirely of zero values. It also noteworthy that we adopted these strength values (i.e., $\{-3, -2, -1, 1, 2, 3\}$) for the cognitive mapping experiment according to the implications presented by [13]. As they reported, the strengths range from -3 to -1, can indicate the negative causal relationships, and from +1 to +3 for positive causal relationships. For example, a participant can hold a strong negative belief (with the strength of -3) or positive belief (with the strength of +3) for a particular case according to his/her opinion.

2.2 Cognitive maps

A cognitive map originally conceptualized by [29] is a graphical structure that allows illustrating the knowledge and beliefs of human learning and behavior [9]. A cognitive map is produced around a specific problem of interest by an individual or a group who are familiar in the relevant field. Accordingly, participants can organize, visualize, and share their experiences, perceptions, and interpretations [28]. The cognitive map consists of nodes representing the variables and a set of directional edges representing the causal relationships among the variables [23]. Also, the edges are associated with numerical values (weights) representing the strength of the causal relationship.

In our data sample, the cognitive maps have been created by individuals considering the impacts of specific 12 strategic issues (chosen by each individual from a pre-defined list of 40 strategic issues) on each other and on the TCSR during the business simulation task. Therefore, the nodes in the cognitive maps represent those 12 strategic issues plus the TCSR. An edge (linkage) with arrowhead between two nodes represents the direction of an effect (causal), and its weight the strength of the causal relation. Figure 1 displays an example of a cognitive map containing positive and negative causal relationships between the elements with associated strengths.

2.3 Inter-causal relationships

Inter-causality is a relationship between one causation and another such that the existence of the former in a cognitive maps implies the existence of the latter. This type of relationship is not directly visible in individual causal maps, but the knowledge of the existence of such relationships can provide valuable insights into the shared cognitive structure of the group under analysis. We should also point out

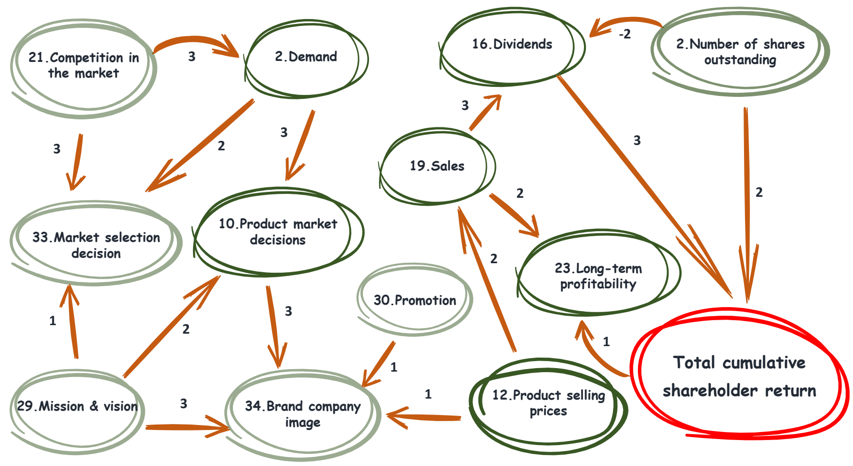

Fig. 1 A cognitive map example in the data collected through the strategic business simulation task.

that the inter-causal relationships are not direct ones, that is they might not be a part of a "causality chain" within the cognitive maps. They represent a coexistence type of relationship between causal relationships in the cognitive structures of individuals and as such the pairs of causal relationships can have different strengths and can even be independent of each other (causality-wise) in the cognitive maps. The essential feature we are investigating by inter-causal relationship is the existence of both causal relationships in the cognitive structures of individuals represented by cognitive maps. It is also possible to examine whether the existence of one relationship seems to be a necessary or sufficient condition for the existence of the other across the cognitive maps (or individual cognitive structures they represent) within the analyzed group. This study attempts to provide a method to detect and interpret such inter-causal relationships in the cognitive maps.

2.4 Set-theoretic consistency and coverage measures

This study mainly focused on the consistency and coverage measures in fuzzy set-theoretic qualitative comparative analysis (fsQCA) that were originally defined by Ragin in [21]. fsQCA is a powerful approach that applies a holistic perspective to acquire similarities and differences through the cases. The fsQCA attempts to interpret causal (cause-effect) relationships between predictor and outcome by identifying which conditions are sufficient or necessary to produce the outcome [24].

Consistency and coverage are two important notions in fsQCA. Let us consider we have a set X of observations available and we are interested in two features of these observations - feature $\mathcal{P}$ and feature $\mathcal{Q}$. We assume that the feature $\mathcal{P}$ can be represented by the subset P of observations that have this feature, $\mathcal{P} \sim P \subseteq X$, and similarly $\mathcal{Q} \sim Q \subseteq X$. Alternatively we can also allow for the observations to have the features only partially, in which case P and Q would be fuzzy subsets of X, in other words $P \subseteq_F X$ or $Q \subseteq_F X$, where for any $x \in X$ we can denote the membership degree of x to P as $P(x) \in [0, 1]$ and its membership degree to Q as $Q(x) \in [0, 1]$.

We are now interested in knowing whether the feature $\mathcal{P}$ can be considered a necessary or sufficient condition for the feature $\mathcal{Q}$ also being present in the given observation. To investigate this, we can focus on the relationship $\mathcal{P} \Rightarrow \mathcal{Q}$ and examine its correspondence with the available data. In other words if we are interested to see whether $\mathcal{P}$ is a sufficient condition for $\mathcal{Q}$, we need to focus on the $P \subseteq Q$ relationship and if $\mathcal{P}$ being a necessary condition for $\mathcal{Q}$ is of interest, we need to focus on $Q \subseteq P$. Set-theoretic consistency refers to a proportion of cases of $\mathcal{P}$ coinciding with $\mathcal{Q}$ in all cases of $\mathcal{P}$ in the data. In other words, it provides a measure of empirical evidence supporting the claim investigated (for example, $P \subseteq Q$). If the consistency value is low for a causal relation, then the empirical evidence does not support the existence of the given causal configuration. This means that the existence of $\mathcal{P}$ is not sufficient for the outcome of $\mathcal{Q}$ to be present. Besides, coverage refers to the proportion of the cases of the outcome $\mathcal{Q}$ that are associated with $\mathcal{P}$ considering all cases of $\mathcal{P}$ in the data [23, 12]. Coverage often works against the consistency, which means high coverage may have low consistency and vise versa [11].

To calculate the consistency and coverage measures, we used the standard formulas presented in [26] as in the following way:

$$Consistency(\mathcal{P} \Rightarrow \mathcal{Q}) = \frac{Card(P \cap Q)}{Card(P)} = \frac{\sum_{i=1}^{n} \min(P(x_i), Q(x_i))}{\sum_{i=1}^{n} P(x_i)} \tag{1}$$

$$Coverage(\mathcal{P} \Rightarrow \mathcal{Q}) = \frac{Card(P \cap Q)}{Card(Q)} = \frac{\sum_{i=1}^{n} \min(P(x_i), Q(x_i))}{\sum_{i=1}^{n} Q(x_i)} \tag{2}$$

where P and Q are two fuzzy sets on X. Here we assume that $Card(P) = \sum_{x \in X} P(x) \neq 0$ and $Card(Q) = \sum_{x \in X} Q(x) \neq 0$ with respect to the relation $P \Rightarrow Q$. When $P \cap Q = P$, then $Consistency(P \Rightarrow Q) = 1$ (perfect consistency), and this implies that there is no evidence that contradicts the given relationship in the data[1], we can also conclude that $\mathcal{P}$ is a sufficient condition for Q. Also, $Coverage(P \Rightarrow Q) = 1$ implies that $P \cap Q = Q$ and thus we can also conclude that $\mathcal{P}$ is a necessary condition for Q. If there are other "causes" for Q, then the coverage score could be less than 1. A relation with the consistency of 1 and coverage of 1 would be an ideal case indicating that P is the only cause for Q, and there are no counterexamples from the data [25].

In general, we prefer to get a good balance from various consistency and coverage ranges for a particular situation where the outcome is compelling theoretically and

[1] If P and Q are fuzzy sets on X then $P \cap Q$ is a fuzzy set on X as well and its membership function is defined, for the purpose of our calculations, using the min t-norm, that is for any $x \in X$ we have $(P \cap Q)(x) = \min\{P(x), Q(x)\}$.

empirically. If the relation has very high consistency but with low coverage, that does not describe many cases at all, and the relationship might be too weak. In contrast, if the case has very high coverage with low consistency, that also indicates a weak relationship because there is no sufficient evidence from the data.

2.5 Hypothesis models

The primary goal of this study, as previously noted, was to identify the inter-causal relationships. Accordingly, we developed two hypotheses regarding the shape of the relationship from one causation to another and tested them with the empirical data. The other two possible hypotheses (positive implies negative, and negative implies positive) are not investigated to keep the presentation of the results simple and the length of the chapter reasonable. As the aim of this chapter is to introduce the necessary methodology and show an example of its performance, the focus on the following two hypotheses is sufficient:

- $Hypothesis$ 1 (H_1): If $C_i \rightarrow C_j$ is positive then $C_p \rightarrow C_q$ is positive
- $Hypothesis$ 2 (H_2): If $C_i \rightarrow C_j$ is negative then $C_p \rightarrow C_q$ is negative

where, C_i, C_j, C_p and C_q indicate four different strategic variables (elements) and $C_i \rightarrow C_j$ and $C_p \rightarrow C_q$ indicate two different causal relations for i, j, p, and q ($i \neq p$ and $j \neq q$) in a map.

Based on our data sample, the effect from one variable to another might be positive or negative. Nonexistent effects (i.e., effects with the strength of zero) are not considered in the subsequent analysis. Nevertheless the proposed methodology can also process the absence of a causal relationship as a part of the investigated inter-causal relationships. Therefore, we consider positive and negative weights on the causal relationships to define the hypotheses. Accordingly, H_1 indicates that the existence of a positive causal relation implies the existence of another positive one, and H_2 indicates that the existence of a negative causal relationship implies the other one to exist too and to be negative. In fact, these hypotheses allow us to identify positive and negative inter-causal relationships.

2.6 Research process

We started the analysis by collecting the frequency of each causal relationship for each strength value going through all adjacency matrices of the cognitive maps. A strength (weight) value for a particular causal relationship can vary from -3 to 3, and it is possible that across the individual cognitive maps the same causal relationship appears several or many times with different strengths. For example, consider the frequency vector for a causal relationship, $(2, 1, 2, 23, 8, 19, 16)$ for the strengths vector $(-3, -2, -1, 0, 1, 2, 3)$. This indicates that 2 individuals weighted the causal strength by −3, 1 individual weighted −2 and so on for the considered causal relation during the simulation process. This example is graphically presented in Figure 2. In this way, we can also identify how many times a given causal relationships is positive, negative, or considered nonexistent (strength value of 0).

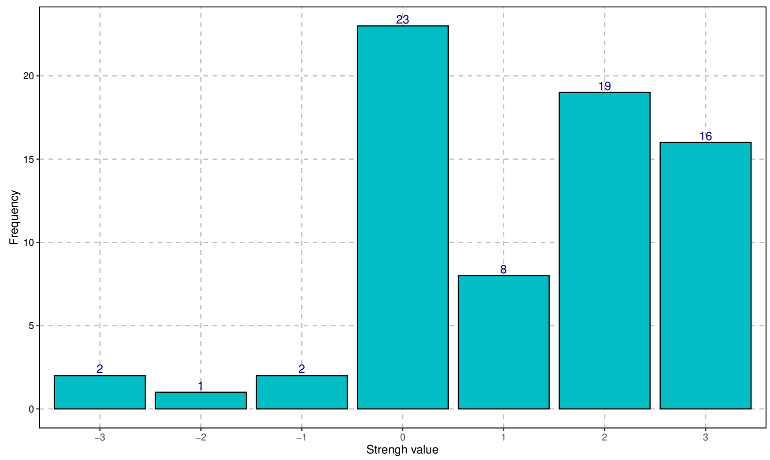

Fig. 2 An example of frequency of each strength value for a selected causal relation

Once the frequencies of different strengths of each investigated causal relationship were collected and visualized using histograms, it is easy to filter out those causal relationships that are not considered to exist by any of the individuals (strength frequency vector $(0,0,0,71,0,0,0)$ in our case with 71 decision-makers). For those causal relationships that were assigned non-zero strength at least once we can proceed to define the membership functions representing the "positive" or "negative" causal effects to be able to investigate hypotheses 1 and 2. There are different types of membership functions that characterize different types of fuzzy sets. As one of them, the trapezoidal membership function is commonly used in current applications. The 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:

$$\mu(x) = \Pi(x;\alpha,\beta,\gamma,\delta) = \begin{cases} 0 & \text{if } x \le \alpha \text{ or } x \ge \delta \\ \frac{x-\alpha}{\beta-\alpha} & \text{if } \alpha \le x \le \beta \\ 1 & \text{if } \beta \le x \le \gamma \\ \frac{\delta-x}{\delta-\gamma} & \text{if } \gamma \le x \le \delta \end{cases} \tag{3}$$

In our study, the criteria to form the trapezoidal fuzzy sets were based on the frequency of the strengths of each causal relation and the linguistic labels positive and negative. It is worth to mention here that we used these linguistic labels to reveal reasonable characteristics of the causalities in the used cognitive maps. To compute the fuzzy numbers with the trapezoidal membership function, we designed its significant values using expert knowledge, (0, 1, 3, 3) for positive and (-3, -3, -1, 0) for negative (i.e., $\mu_{positive} \sim \Pi(x; 0, 1, 3, 3)$ and $\mu_{negative} \sim \Pi(x; -3, -3, -1, 0)$). Once the membership values for all observations were obtained, consistency and coverage values were computed using formulas (1) and (2).

Next, we evaluated the validity of the hypotheses based on the consistency and coverage values obtained. We prioritized the consistency first during the evaluation and then the coverage scores to gain additional support for each hypothesis. Concerning consistency, a high value makes investigated claim stronger. A specific value for the required consistency can also be defined depending on the cases we evaluated. In this study, we considered the evidence in favor of the hypotheses to be sufficient and reasonable if the corresponding rules have consistency value ranged from *acceptable* through *high* to *excellent*. In this way, we collected all of inter-causal relationships into excellent, high and acceptable ranges if their consistency value was in the $[0.9, 1]$, $[0.75, 0.9)$ and $[0.6, 0.75)$ intervals respectively. Besides that, we considered that low consistencies do not support the validity of the cases. In contrast to the consistency thresholds, we assumed that an acceptable coverage distributes between 0.25 and 0.65 ($0.25 \leq$ coverage ≤ 0.65) and explains the existence of particular inter-causal relationships. This way we evaluate the validity of each hypothesis and next section presents and discusses the results of the analysis.

3 Results and discussion

This section analyzes and discusses the results obtained from the proposed framework applied for identifying essential inter-causal relationships in the shared cognitive maps. We drove our analysis based on two hypotheses–accordingly, we examined 3932 relationships between perceived causal relations under H_1 and 176 under H_2 extracted from the cognitive maps in the data. Having this, we calculated consistency and coverage values for each of those relationships to determine whether it is a significant relationship or not (i.e., to validate each of the hypotheses). In terms of the consistency, initially, three different boundaries (for acceptable, high, and excellent) were set for categorizing the significance of the inter-causal relationships under each hypothesis. In this sense, we discuss all cases over four different intervals of consistency, $[0, 0.6)$, $[0.6, 0.75)$, $[0.75, 0.9)$ and $[0.9, 1]$ and they reflect the weak, acceptable, high and excellent levels of the evidence. In addition to that, we consider three levels of coverage scores as $[0, 0.25)$, $[0.25, 0.65]$ and $(0.65, 1]$ to reflect the relevance of the coverage together with consistency.

In the analysis, we first examined the inter-causal relationships under H_1 and an overview of the found results is presented in Table 1. This table summarizes the results of the relative number of inter-causal relationships recognized within the different ranges of consistency and coverage. These results are displayed by percentages with respect to the total number of cases we investigated.

From Table 1, it is apparent that small amounts of inter-causal relationships ($2.01\%[= 0.2\% + 0.64\% + 1.07\% + 0.1\%] \sim 79$ cases) have been significant (gaining

Table 1 Inter-causal relationships % detected within different ranges of consistency and coverage scores under H_1.

		Coverage		
		> 0.65	$[0.25, 0.65]$	$[0, 0.25)$
	≥ 0.9	0.0%	0.20%	0.79%
Consistency	$[0.75, 0.9)$	0.0%	0.64%	1.55%
	$[0.6, 0.75)$	0.1%	1.07%	2.14%
	$[0, 0.6)$	5.14%	37.03%	51.35%

consistency ≥ 0.6 and coverage ≥ 0.25) under H_1. In particular, there are 0.2% (~ 8) inter-causal relationships found with excellent consistencies (with consistency value 0.9 or higher) and reasonable coverages (coverage $\in [0.25, 0.65]$. Also, 0.64% (~ 25) cases appear to be in the consistency ranged of $[0.75, 0.9)$ and 1.07% (~ 42) cases in the range of $[0.6, 0.75)$ holding sufficient evidence under the H_1. There is no case that has the coverage of 0.65 or more when consistency ≥ 0.75. In summary, we can see that most of the cases (93.52%[= 5.14% + 37.03% + 51.35%] $\sim$ 3677) do not have enough support in the data based on the the consistency values (consistency < 0.6). Even though some cases (4.48% $\sim$ 176) have sufficient evidence in their favor in the data (consistency ≥ 0.6), they seem to be too weak in terms of the coverage scores (consistency < 0.25). Besides, Table 2 presents the overview of the results of the inter-causal relationships found within the different intervals of set-theoretic scores under H_2. According to the table information, it seems there is a considerable number of cases (11.93%[= 5.11% + 3.98% + 0.57% + 1.7% + 0.57%] $\sim$ 26) compared to the all cases investigated which has sufficient support in the data (consistency ≥ 0.6) and reasonable coverages (coverage $\in [0.25, 0.65]$). It is interesting to see that 5.11% ($\sim$ 9) cases have obtained excellent consistencies and high coverages under H_2. Literally, all of these inter-causal relationships except one hold the consistency of 1 and coverage of 1. These results are discussed further in the coming subsections. Next, we thoroughly discuss the most important results summarized in the above tables under H_1 and H_2 separately.

Table 2 Inter-causal relationships % detected within different ranges of consistency and coverage scores under H_2.

		Coverage		
		> 0.65	$[0.25, 0.65]$	$[0, 0.25)$
	≥ 0.9	5.11%	3.98%	8.52%
Consistency	$[0.75, 0.9)$	0.0%	0.57%	0.0%
	$[0.6, 0.75)$	0.57%	1.7%	0.0%
	$[0, 0.6)$	13.64%	30.11%	36.36%

3.1 Inter-causal relationships under H_1

We have scrutinized numerous inter-causal relationships using the set-theoretic scores over the hypothesis H_1, and found sufficient and reasonable evidence on 255 cases. Therefore, interpretation and exhibition of the all of such cases are a real challenge and we summarize and discuss the essential cases that are concerned with what must be reported.

From H_1, we expected to investigate possible linkages between positive causal relations in the cognitive maps. Figure 3 displays the consistency and coverage values obtained under H_1 on the selected 40 inter-causal relationships within all ranges of the set-theoretic scores. In the figure, the boundaries for the consistency and coverage ranges are presented by horizontal dash-lines with different colors. From this figure, one can clearly understand how the set-theoretic scores distribute over each inter-causal relationship and see which of them have sufficient and reasonable evidence in favor of the existence. Let us consider some examples in each range of the consistency and coverage scores. Table D.1 in the Appendix provides the practical meaning of the integer labels of the strategic issues for easier presentation of the investigated inter-causal relationships.

It is apparent that some cases have excellent support for their existence from very high consistency and reasonable coverage scores. For example, the relation $(2 \rightarrow 41) \Rightarrow (1 \rightarrow 41)$ holds the consistency of 0.92 and coverage of 0.4. Also, the cases $(20 \rightarrow 37) \Rightarrow (15 \rightarrow 37)$, $(23 \rightarrow 16) \Rightarrow (16 \rightarrow 41)$ and $(8 \rightarrow 41) \Rightarrow (21 \rightarrow 41)$ have fully consistent support (consistency = 1) associated with appropriate coverages (0.4, 0.42 and 0.5, respectively). Moreover, we can observe that some relationships for examples, $(12 \rightarrow 41) \Rightarrow (10 \rightarrow 41)$ and $(2 \rightarrow 1) \Rightarrow (16 \rightarrow 41)$ have a considerable support from the evidence obtaining acceptable consistencies (0.62 and 0.65) and reasonable coverages (0.26 and 0.56). Besides, there are fully coverage scores (coverage = 1) on the relations $(12 \rightarrow 2) \Rightarrow (10 \rightarrow 2)$ and $(20 \rightarrow 23) \Rightarrow (10 \rightarrow 2)$ but corresponding consistencies (0.33 and 0.25) that are not on the acceptable level. This indicates that there is no sufficient evidence in favor these relationships. Also, considering the rest of the consistency values that are less than 0.6, we do not find enough evidence in favor of corresponding relationships.

To get more insights on the results under H_1, we present all cases with excellent consistencies (i.e., consistency $\geq$ 0.9) in Table 3. We already discussed the cases that hold the perfect consistencies and reasonable coverage scores (see the bold case in the table). Focusing on other information in the table, however, it is apparent that most cases have a consistency of 1 but shallow coverage (less than 0.25), for example, $(21 \rightarrow 2) \Rightarrow (23 \rightarrow 41)$. This means that even though the relationship has a consistency of 1, particular condition is empirically trivial (irrelevant).

Table 4 illustrates the interpretation of the selected inter-causal relationships along with their respective consistencies and coverages under H_1. The identified inter-causal relationships that are supported by excellent consistency and appropriate coverage appear logical. Such inter-causal relationships reveal deeper structural meanings in the causal maps. The direct causal effect of demand on shareholder return $(2 \rightarrow 41)$ accompanied with causal effect of market share on shareholder return

(1 → 41) refers to understanding that shareholder return is dependent on size of the market and firm's share of it.The inter-causal relationship of direct effect of corporate tax rate on equity ratio (20 → 37) and effect of debt on equity ratio (15 → 37) the underlying logic might be the knowledge about issues that influence firms' solvency. The inter-causal relationship of the effect of profitability on dividends (23 → 16) and the effect of dividends on shareholder return (16 → 41) is very clear. When the effect of in-house R&D on shareholder return (8 → 41) is accompanied with the effect of intense competition on shareholder return (21 → 41), it can be understood that these causalities together signal perception of innovation as competitive strategy. We can clearly see that the above discussed identified inter-causal relationship with high consistency can be interpreted in the framework of the actual simulation task and can be considered to "make sense" in the simulated reality. We should, however, remark here, that the proposed methodology for the identification of inter-causal relationships can also find highly consistent inter-causal relationships that might not be easily interpretable in the context of the given system/simulation/economic theory. But even this does not mean that such relationships are coincidental or incorrectly identified. We discuss this issue more in the following subsection. The fact that inter-causal relationships are ones of coexistence rather than of "causality chains" needs to be taken into account in the interpretation of these relationships. Obviously, inter-causal relationships with low consistency and insufficient coverage should not be considered to appear in the shared cognitive structure of the group.

Table 3 All the cases with excellent consistency values under H_1.

$(C_i \to C_j) \Rightarrow (C_p \to C_q)$	Consistency	Coverage	$(C_i \to C_j) \Rightarrow (C_p \to C_q)$	Consistency	Coverage
(1 → 24) ⇒ (16 → 41)	1	0.08	(3 → 12) ⇒ (16 → 41)	1	0.09
(8 → 41) ⇒ (1 → 41)	1	0.10	(8 → 41) ⇒ (2 → 41)	1	0.23
(8 → 41) ⇒ (21 → 41)	**1**	**0.50**	(11 → 2) ⇒ (2 → 19)	1	0.16
(12 → 1) ⇒ (16 → 41)	1	0.14	(15 → 16) ⇒ (16 → 41)	1	0.02
(15 → 16) ⇒ (19 → 1)	1	0.06	(15 → 16) ⇒ (19 → 24)	1	0.05
(15 → 16) ⇒ (24 → 41)	1	0.03	(15 → 16) ⇒ (30 → 19)	1	0.07
(15 → 16) ⇒ (33 → 1)	1	0.10	**(15 → 16) ⇒ (38 → 41)**	**1**	**0.33**
(15 → 41) ⇒ (19 → 41)	1	0.19	(15 → 41) ⇒ (24 → 41)	1	0.14
(19 → 16) ⇒ (16 → 41)	1	0.07	(19 → 22) ⇒ (23 → 41)	1	0.14
(20 → 37) ⇒ (2 → 1)	1	0.12	**(20 → 37) ⇒ (15 → 37)**	**1**	**0.40**
(20 → 37) ⇒ (16 → 41)	1	0.05	(20 → 37) ⇒ (23 → 41)	1	0.04
(21 → 2) ⇒ (2 → 19)	1	0.12	(21 → 2) ⇒ (23 → 41)	1	0.07
(21 → 23) ⇒ (23 → 41)	1	0.09	(22 → 16) ⇒ (16 → 41)	1	0.09
(23 → 16) ⇒ (16 → 41)	**1**	**0.42**	**(23 → 24) ⇒ (24 → 41)**	**1**	**0.28**
(23 → 37) ⇒ (16 → 41)	1	0.09	(29 → 10) ⇒ (23 → 41)	1	0.18
(30 → 41) ⇒ (1 → 41)	1	0.10	(33 → 12) ⇒ (23 → 41)	1	0.11
(33 → 41) ⇒ (1 → 41)	1	0.13	**(2 → 41) ⇒ (1 → 41)**	**0.92**	**0.40**

Table 4 Interpretation of chosen inter-causal relationships and their set-theoretic scores under H_1; P-M decisions stands for product-market decisions, LTP for long-term profitability, TCSR represents total cumulative shareholder returns. All causal relationships have positive strength.

Antecedent causal relationship			Consequent causal relationship		Consistency	Coverage
2. Demand	$\rightarrow$ 41. TCSR	$\Rightarrow$	1. Market share	$\rightarrow$ 41. TCSR	0.92	0.40
20. Corporate tax rate	$\rightarrow$ 37. Equity Ratio	$\Rightarrow$	15. Long-term debt	$\rightarrow$ 37. Equity Ratio	1.00	0.40
23. LTP	$\rightarrow$ 16. Dividends	$\Rightarrow$	16. Dividends	$\rightarrow$ 41. TCSR	1.00	0.42
8. In-house R&D	$\rightarrow$ 41. TCSR	$\Rightarrow$	21. Market competition	$\rightarrow$ 41. TCSR	1.00	0.50
12. Product selling prices	$\rightarrow$ 41. TCSR	$\Rightarrow$	10. P-M decisions	$\rightarrow$ 41. TCSR	0.62	0.26
2. Demand	$\rightarrow$ 16. Market share	$\Rightarrow$	16. Dividends	$\rightarrow$ 41. TCSR	0.65	0.56
12. Product selling prices	$\rightarrow$ 2. Demand	$\Rightarrow$	10. P-M decisions	$\rightarrow$ 2. Demand	0.33	1.00
20. Corporate tax rate	$\rightarrow$ 23. LTP	$\Rightarrow$	10. P-M decisions	$\rightarrow$ 2. Demand	0.25	1.00
21. Market competition	$\rightarrow$ 2. Demand	$\Rightarrow$	23. LTP	$\rightarrow$ 41. TCSR	1.00	0.07

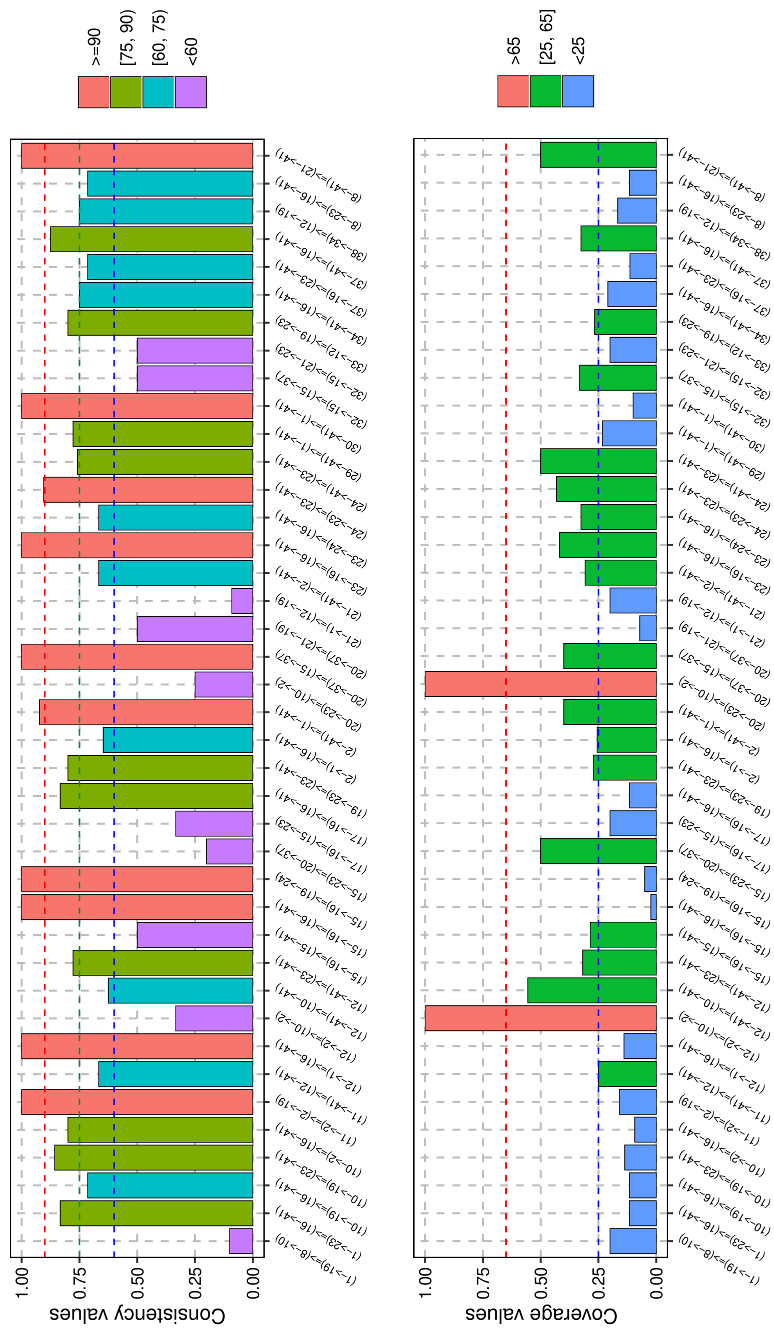

Fig. 3 Consistency and coverage values on the selected 40 inter-causal relationships under H_1

3.2 Inter-causal relationships under H_2

Turning now to empirical evidence on the evaluation of H_2, we have found sufficient and reasonable evidence on 36 cases. Figure 4 illustrates the consistency and coverage scores on the selected 40 inter-causal relationships. In this figure, we specifically focused on eight ideal inter-causal relationships (consistency = 1 and coverage = 1) over H_2. This is an interesting result we found, and we discuss them in detail later. Apart from this, the cases $(20 \rightarrow 37) \Rightarrow (17 \rightarrow 16)$ and $(8 \rightarrow 41) \Rightarrow (1 \rightarrow 41)$ have strong support from consistency of 1 and considerably high coverages of 0.67 and 0.5, respectively. We also can see there is sufficient evidence in favor of some cases for example, $(12 \rightarrow 2) \Rightarrow (20 \rightarrow 23)$ obtaining consistency of 0.67 and reasonable coverage of 0.5. In contrast, there is weak evidence from the consistency in some cases (e.g., $(15 \rightarrow 41) \Rightarrow (15 \rightarrow 16)$) even though they have reasonable coverages. Also, the relations such as $(10 \rightarrow 19) \Rightarrow (21 \rightarrow 1)$, $(2 \rightarrow 12) \Rightarrow (21 \rightarrow 12)$ hold perfect consistencies with strong coverage values revealing that existing evidence do not support the particular relations. In this way, we identified all significant inter-causal relationships under H_2.

Table 5 illustrates the interpretation of the selected found inter-causal relationships under H_2 and their respective consistencies and coverages. We need to keep in mind that the inter-causal relationships analysed here do not suggest the existence of a "causality chain" from one causal relationship to the other. The existence of consistent inter-causal relationship with high coverage simply means that the existence of the first (antecedent) causal relationship in a causal map implies that the second (consequent) causal relationship can be found there too. This explains why even thought the inter-causal relationships in Table 5 have excellent consistencies and coverages, they appear irrelevant and meaningless. The face validity check of the inter-causal relationship needs to be performed in a different way than one would perform a validity check of causal relationships. It might not make sense to assess the co-existence of a pair of causal relationship in the shared cognitive structure against the theoretical assumptions. The inter-causal relationship does not suggest a causal link between the causal relationships. Their existence (with high consistency and coverage) should instead be interpreted in the cognitive context as representing the (mis)concepts of the decision-makers possibly shared in the group.

Looking at the mere comparison of the number of possible inter-causal relationships under H_1 that focuses in positive causal relationships and H_2 that focuses on negative ones it is striking how much the number of causal relationships differs between H_1 and H_2. It appears that the majority of the respondents find it easier to focus on positive causal relationships, or they only consider a strength of the relationship, but not its sign. Apparently, the respondents find it difficult to formulate negative causal relationships in their cognitive maps, or may even misinterpret the actual meaning of a negative strength of a causal relationship. For example, there is one inter-causal relationship where negative impact of sales on dividends $(19 \rightarrow 16)$ is associated with negative impact of promotion on sales $(30 \rightarrow 19)$. Still this provides us with valuable insights into the shared cognitive structure of the group and the (in)consistency thereof with our expectations and with the relevant economic theories.

Table 5 Interpretation of chosen inter-causal relationships and their set-theoretic scores under H_2; P-M decisions stands for product-market decisions, LTP for long-term profitability. All causal relationships have negative strength.

Antecedent causal relationship				Consequent causal relationship			Consistency	Coverage
10. P-M decisions	→	2. Demand	⇒	19. Sales	→	23. LTP	1.00	1.00
10. P-M decisions	→	19. Sales	⇒	19. Sales	→	16. Dividends	1.00	1.00
10. P-M decisions	→	19. Sales	⇒	30. Promotion	→	19. Sales	1.00	1.00
19. Sales	→	16. Dividends	⇒	10. P-M decisions	→	19. Sales	1.00	1.00
19. Sales	→	16. Dividends	⇒	30. Promotion	→	19. Sales	1.00	1.00
19. Sales	→	23. LTP	⇒	10. P-M decisions	→	2. Demand	1.00	1.00
30. Promotion	→	19. Sales	⇒	10. P-M decisions	→	19. Sales	1.00	1.00
30. Promotion	→	19. Sales	⇒	19. Sales	→	16. Dividends	1.00	1.00

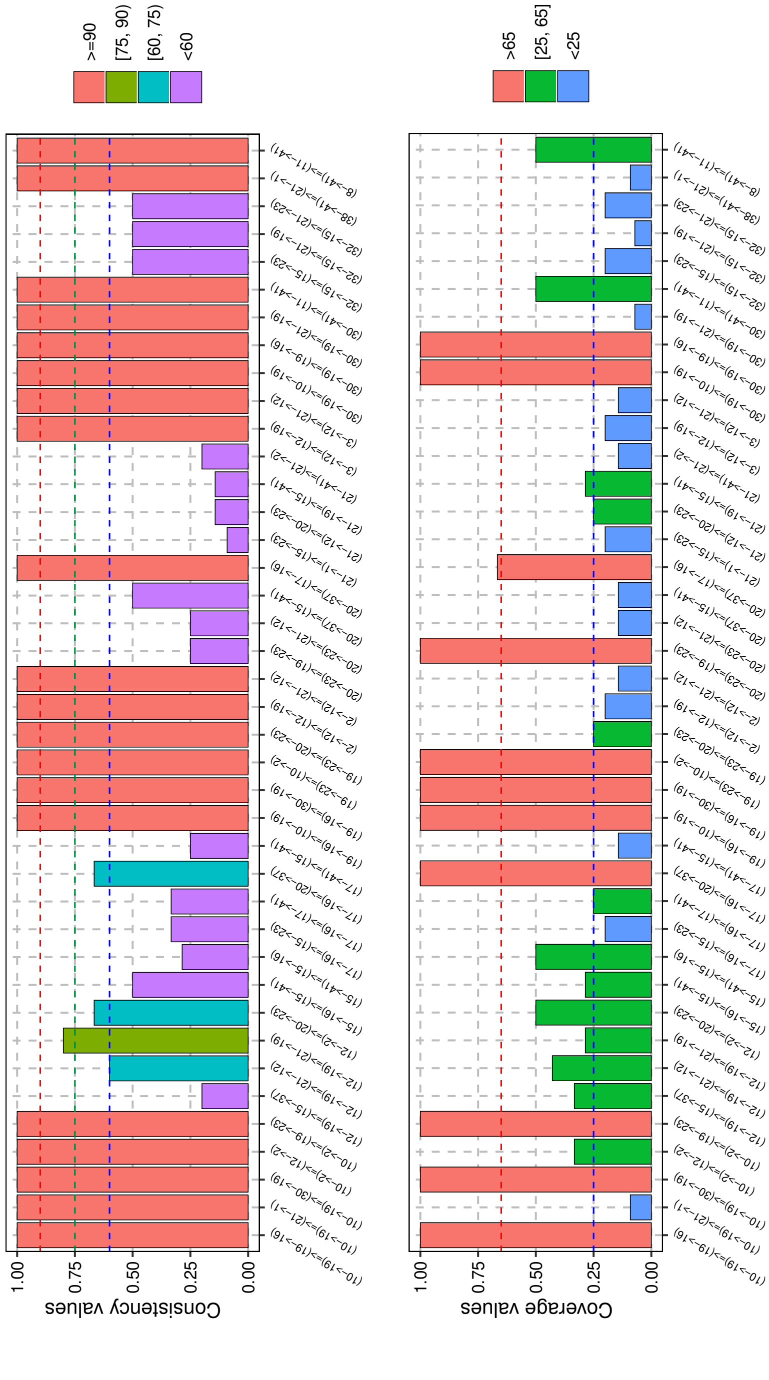

Fig. 4 Consistency and coverage values on the selected 40 inter-causal relationships under H_2

4 Conclusion and future directions

The purpose of this study was to investigate the relationships between causal relationships (i.e., inter-causal relationships) in the individual cognitive maps and their existence within the shared cognitive structure in the given group of decision-makers. To accomplish this, we developed a methodology using set-theoretic consistency and coverage measures. The developed method was employed with the empirical data of cognitive maps collected through a strategic decision-making process. Then, the analysis was carried out by establishing two hypotheses based on the positive and negative characteristics of each relationship. From the empirical evidence obtained, the findings with set-theoretic consistency and coverage scores suggest that there are some strong (with strong support from the data) inter-causal relationships in the cognitive maps. In particular, we found sufficient and reasonable evidence on 255 inter-causal relationships under H_1 and 36 inter-causal relationships under H_2.

We are aware that our methodology may have some limitations. For example, the information represented in cognitive maps largely depends on the participants' knowledge, experience, and beliefs. In that case, we cannot always guarantee the accuracy of the data of all maps concerning the particular situation. Another thing is that the proposed approach results would be increasingly complex and challenging to interpret when the number of concepts increases (i.e., causal conditions increase). Despite this, the proposed method for the identification of inter-causal relationships is helpful in revealing the networked structure of the perceived causalities. Deeper understanding of these inter-relatedness of the perceived causalities (operationalized with inter-causal relationships as the coexistence of the causal relationships within a cognitive structure) gives better description of the respondents' overall logic and of the shared cognitive structure in the group than the assessment of separate causal relations. This is a significant methodological contribution to the study of cognitive maps.

As far as we know, no other study has attempted to investigate the inter-causal relationships in cognitive maps. We believe that the presented approach in this study could be useful in cognitive mapping related studies to be applied for scrutinizing and interpreting the inter-causal relationships in a meaningful way. For example, a cognitive mapping technique can be used to study sustainable tourism policies [7]. Because of the complexity of underpinning policies used in cognitive maps, we are confident that our method has the potential to scrutinize the policy issues and their relations so that policymakers can easily reach their goals. Furthermore, we also recommend possibility of further research is undertaken in large manufacturing systems where a chemical process is conceptualized in fuzzy cognitive maps (see example, [27]). Regarding this, the most influential chemicals elements and their inter-causal relations can be examined using the proposed method and, it would make the manufacturing process more effective and success controlling the settings of the crucial factors and actions.

References

[1] Avdeeva ZK, Kovriga SV (2018) On Governance Decision Support in the Area of Political Stability Using Cognitive Maps. IFAC-PapersOnLine 51(30):498–503, DOI 10.1016/j.ifacol.2018.11.277
[2] Ayala AP, Azuela JHSA, Gutiérrez A (2007) Cognitive maps: an overview and their application for student modeling. Computación y Sistemas 10
[3] Bergman JP, Knutas A, Luukka P, Jantunen A, Tarkiainen A, Karlik A, Platonov V (2016) Strategic interpretation on sustainability issues-eliciting cognitive maps of boards of directors. Corporate Governance 16(1):162–186
[4] Bergman JP, Luukka P, Jantunen A, Tarkiainen A (2020) Cognitive diversity, managerial characteristics and performance development among the clean-tech. International Journal of Knowledge-Based Organizations 10(1), DOI 10.4018/IJKBO.2020010101
[5] Bevilacqua M, Ciarapica FE, Mazzuto G (2012) Analysis of injury events with fuzzy cognitive maps. Journal of Loss Prevention in the Process Industries 25:677–685
[6] Carvalho JP, Tome JAB (2000) Fuzzy mechanisms for qualitative causal relations. Berlin Heidelberg: Springer.
[7] Farsari I, Butler RW, Szivas E (2010) The use of cognitive mapping in analysing sustainable tourism policy: Methodological implications. Tourism Recreation Research pp 145–160
[8] Froelich W, Papageorgiou EI, Samarinas M, Skriapas K (2012) Application of evolutionary fuzzy cognitive maps to the long-term prediction of prostate cancer. Applied Soft Computing 12:3810–3817
[9] Gray SA, Zanre E, Gray SRJ (2014) Fuzzy cognitive maps as representation of mental models and group beliefs. Fuzzy Cognitive Maps for Applied Sciences and Engineering pp 29–48
[10] Gray SA, Gray S, De Kok JL, Helfgott AER, O'Dwyer B, Jordan R, Nyaki A (2015) Using fuzzy cognitive mapping as a participatory approach to analyze change, preferred states, and perceived resilience of social-ecological systems. Ecology and Society 20(2), DOI 10.5751/ES-07396-200211
[11] Kent R (2008) Using fsQCA: A Brief Guide and Workshop for Fuzzy- Set Qualitative Comparative Analysis (Teaching Notes). University of Manchester
[12] Kumbure MM, Tarkiainen A, Luukka P, Stoklasa J, Jantunen A (2020) Relation between managerial cognition and industrial performance: An assessment with strategic cognitive maps using fuzzy-set qualitative comparative analysis. Journal of Business Research 114:160–172
[13] Langfield-Smith K, Wirth A (1992) Measuring differences between cognitive maps. Journal of the Operational Research Society 43:1135–1150
[14] Mendonca M, Angelico B, Arruda LVR, Neves FJ (2013) A dynamic fuzzy cognitive map applied to chemical process supervision. Engineering Applications of Artificial Intelligence 26:1199–1210

[15] Mohammed S, Ferzandi L, Hamilton K (2010) Metaphor no more: A 15-year review of the team mental model construct. Journal of Management 36:876–910

[16] Motlagh O, Tang SH, Ismail N, Ramil AR (2012) An expert fuzzy cognitive map for reactive navigation of mobile robots. Fuzzy Sets and Systems 201:105–121

[17] Mourhir A, Rachidi T, Papageorgiou EI, Karim M, Alaoui FS (2016) A cognitive map framework to support integrated environmental assessment. Environmental Modelling and Software 77:81–94, DOI 10.1016/j.envsoft.2015.11.018

[18] Nápoles G, Grau I, Bello R, Grau R (2014) Two-steps learning of Fuzzy Cognitive Maps for prediction and knowledge discovery on the HIV-1 drug resistance. Expert Systems with Applications 41(3):821–830, DOI 10.1016/j.eswa.2013.08.012

[19] Papageorgiou EI, Froelich W (2012) Multi-step prediction for pulmonary infection with the use of evolutionary fuzzy cognitive maps. Neurocomputing 92:28–35

[20] Papageorgiou EI, Markinos AT, Gemtos TA (2011) Fuzzy cognitive map based approach for predicting yield in cotton crop production as a basis for decision support system in precision agriculture application. Applied Soft Computing 11:3643–3657

[21] Ragin CC (2008) Redesigning social inquiry: Fuzzy sets and beyond

[22] Robbins SP (2005) Organizational behavior (11th ed.). Upper Saddle River, NJ: Pearson Education.

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

[24] Skaaning SE (2011) Assessing the robustness of crisp-set and fuzzy-set qca results. Sociological Methods & Research 40:391–408

[25] 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

[26] 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 pp 521–526

[27] Stylios CD, Groumpos PP (1998) Application of Fuzzy Cognitive Maps in Large Manufacturing Systems. IFAC Proceedings Volumes 31(20):521–526, DOI 10.1016/S1474-6670(17)41848-9

[28] Tepes A, Neumann MB (2020) Multiple perspectives of resilience: A holistic approach to resilience assessment using cognitive maps in particular engagement. Water Research 178

[29] Tolman EC (1948) Cognitive maps in rats and men. Psychological Review 55(4):189–208

[30] Zhu Q, Wang R, wang Z (2013) A cognitive map model based on spatial and goal-oriented mental exploration in rodents. Behavioural Brain Research 256:128–139

Table D.1 Pool of strategic issues on sustainable return to shareholders.

ID	Strategic issues	ID	Strategic issues
1	Market share	22	Short-term profitability
2	Demand	23	Long-term profitability
3	Own manufacturing	24	Growth of the company
4	Contract manufacturing	25	Employee training and education
5	Inventory management	26	Consumer price elasticity
6	Investment in production and plants	27	R&D employee turnover
7	Number of R&D personnel	28	Wages of R&D employees
8	In-house R&D	29	Mission and vision
9	Buying technology and design licenses	30	Promotion
10	Product-market decisions (technology)	31	Transportation cost
11	Feature offered	32	Interest rates
12	Product selling prices	33	Market selection decisions
13	Logistics priorities	34	Brand, company image
14	Transfer prices	35	Capacity allocation
15	Long-term debt	36	Network coverage
16	Dividends	37	Equity ratio
17	Number of shares outstanding	38	Environmental sustainability
18	Internet loans	39	Supplier selection
19	Sales	40	Supply chain ethics
20	Corporate tax rate	41	Total cumulative shareholder returns
21	Competition in the market		