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Causal maps in the analysis and unsupervised assessment of the development of expert knowledge: Quantification of the learning effects for knowledge management purposes

Mahinda Mailagaha Kumbure [a,*], Anssi Tarkiainen [a], Jan Stoklasa [a,b], Pasi Luukka [a], Ari Jantunen [a]

[a] Business School, LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland
[b] Department of Economic and Managerial Studies, Faculty of Arts, Palacký University Olomouc, Křížkovského 12, 77900 Olomouc, Czech Republic

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ABSTRACT

This study proposes an application of cognitive maps in the representation of cognitive structures of the experts and assessment of their development/modification as a result of a (computer or expert system-assisted) learning process. It strives to identify information needed for the guidance of the process of creation and management of expert knowledge by formal modeling tools. Changes in experts' cognitive structures are assumed to stem from individual and collaborative (group-level) learning. The novel approach to assessing the outcomes of learning reflected as changes in the cognitive structures of experts or groups of experts, modeled by cognitive maps, does not assume any correct or desired outcome of the learning process to be known in advance. Instead, it identifies and analyzes the changes in (or robustness of) the constituents of the cognitive maps from different points of view and allows for quantifying and visualizing the actual effect of the learning. The proposed methodology can identify changes in cognitive diversity, causal structures in terms of causal relations and concepts, and the perceived importance of strategic issues over the learning period. It can also detect which cause–effect relationships have appeared/disappeared considering the pre-/post-mapping design. Thus, it provides an exploratory account on the changes in the cognitive structures of the expert(s) as a result of learning. The applicability of the proposed methods is illustrated in the assessment of the learning outcomes of a group of 71 graduate students who participated in an eight-week business simulation task. The results of the empirical analysis confirm the viability of the proposed methodology and indicate that the students' understanding of the utilized concepts and associated relationships in the decision-making process improved throughout the learning activity, ultimately showing that the course learning has considerably improved students' perception and knowledge. Based on the results, it can be concluded that the proposed approach has the potential to be effective in assessing learning outcomes in teaching–learning activities.

1. Introduction

Expert knowledge development and its efficient management are necessary in all areas of human activity and as such it is studied in various fields, especially in education, andragogy, sociology, and also in a field-specific context of professional training and expertise development, with potentially increasing importance in the design of expert systems and artificial intelligence solutions. Understanding how individuals learn and acquire and enhance their knowledge leads to efficient educational practices and knowledge management. Even though a lot of attention is being paid to the actual processes of learning and teaching ('how' the knowledge is being constructed), their results, that is the outcomes of learning ('what' has been learned), still remain difficult to quantify and thus analyze systematically. Individual perceptions influence the teaching–learning process and are characterized by personal knowledge, experience, and other aspects, such as beliefs, interests, and expectations (Robbins, 2005). Consequently, a situation, a problem, or a concept can be perceived from various angles and perspectives, which might also differ from one person to another. This

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* Corresponding author.
E-mail addresses: mahinda.mailagaha.kumbure@lut.fi (M.M. Kumbure), anssi.tarkiainen@lut.fi (A. Tarkiainen), jan.stoklasa@lut.fi (J. Stoklasa), pasi.luukka@lut.fi (P. Luukka), ari.jantunen@lut.fi (A. Jantunen).

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makes the operationalization of the effects and outcomes of learning demanding. To gain a comprehensive understanding of the effects and outcomes of the teaching–learning process and allow for robust analyses, the concept of cognitive mapping as a participatory method has recently received interest among researchers and scholars (Gray et al., 2015). A cognitive map that acts as a cause-and-effect network of qualitative aspects (Tolman, 1948) supports individuals in visually representing their beliefs, arguments, and understanding of a situation or problem (Kumbure et al., 2022) and as such it can serve as a representation of cognitive structures representing (expert) knowledge in various domains and areas of activities. It is also interesting to note that it can represent the knowledge and various cognitive structures in various stages of the knowledge creation process. As such cognitive maps represent a tool for the assessment of changes and development (a flow-type measure) of expert knowledge. This very aspect of cognitive maps is going to be explored in this paper and methods for their use in the assessment of the outcomes of the teaching–learning process will be proposed. Cognitive maps remain a subject of ongoing research interest in various applications involving social science (e.g., Son et al., 2021), education research (e.g., Nesbit & Adesope, 2006; Sun et al., 2019; Wang et al., 2018), business and management research (e.g., Bergman et al., 2016; Kumbure et al., 2020), healthcare (e.g., Ottink et al., 2022), engineering and technology (e.g., Mendonca et al., 2013; Motlagh et al., 2012), environment research (e.g., Aledo et al., 2015), and computer science (e.g., Budak & Çoban, 2021; Kwon, 2011), to mention a few.

A cognitive map, initially presented by Tolman (1948), is a graphical structure that allows illustrating the knowledge and beliefs of human learning and behavior (Gray et al., 2014). It is created around a specific problem of interest by an individual or a group of individuals who are familiar with the related field. Subsequently, participants can conceptualize, organize, and share their experiences, beliefs, and interpretations in the maps (Tepes & Neumann, 2020). Focusing on the topology of a cognitive map, it includes "nodes" representing the concepts (variables) and a set of "directed edges" representing causal (cause–effect) relationships among the concepts (Schneider & Wagemann, 2012). Also, the edges are linked with numerical values (weights), representing the strength of the causal relationship. Therefore, examining the cognitive maps allows for the evaluation of the causal relationships, their persistence or change, and associated concepts to obtain essential information about the cognition (cognitive structures) of individuals involved in the process and for future operations in the relevant context. Our research explores the changes in cognitive structures (expert knowledge) represented by the causal maps produced at the start and at the end of a teaching–learning activity. The effect of the teaching–learning activity on the expert knowledge is operationalized as change or persistence of the elements and features of the causal maps representing the knowledge at different points in time.

Recently, teaching and learning have become much more accessible and efficient with the advent of modern technological tools (Carstens et al., 2021), and implementing computer-based applications to the learning environment has been a great interest in educational research to date. In particular, computer-supported collaborative learning (CSCL) is recognized as a powerful tool in designing learning practices where the students can effectively enhance their learning (Salovaara & Järvelä, 2003). In the CSCL settings, the work of individual learning (Lou et al., 2001; Novarese, 2012) and collaborative (group-level) learning (Kinchin & Hay, 2005; Sizmur & Osborne, 1997) is frequently regarded as performing a crucial role in students' academic learning. Individual learning refers to a process that involves a change in one's behavior or knowledge (Novarese, 2012). In contrast, collaborative learning is an educational technique in which individuals are set to small groups to enhance their learning by working together (Zambrano R. et al., 2019). It is important to note that the effect of learning on the group-level knowledge and understanding of the key concepts, as well as the effect of learning on the individual level, need to be assessed to be able to manage and optimize the teaching/learning process.

The assessment of learning serves several functions, and the most important is to support learning, assess students' achievements, and maintain standards of the profession (Joughin, 2009). Assessment of the outcomes of a teaching–learning activity thus reflects its on the expert knowledge and the enhancement (change) thereof and as such it is crucial for knowledge management purposes. On the one hand, assessment is the cornerstone of learning since it reveals how successful the teaching–learning process is, but on the other hand, some types of assessment (such as summative tests) have shown to reduce motivation for learning (Dochy, 2009). The mechanisms with which assessment supports learning include (1) assessment ensuring that students engage in specified learning processes, (2) assessment providing feedback to students on their learning, (3) assessment developing students' capacity to evaluate the quality of their own work, and finally, (4) assessment results being used to guide, plan and optimize the teaching process (Joughin, 2009). The importance of the fourth way, i.e., guiding the teacher, is often acknowledged in higher education, but its operationalization is rarely addressed (Joughin, 2009).

In the present study, we develop and demonstrate methods for assessing learning outcomes applicable also in the context of the CSCL that operationalize information for teaching (Joughin, 2009) with the causal mapping technique (Axelrod, 1976). The developed methods meet the characteristics outlined by Dochy (2009) and build on the use of epistemic games (Gordon, 2020) for engaging students in constructing and applying knowledge in the actual case. The causal mapping technique resembles the knowledge maps that have been used for describing target knowledge (Zheng et al., 2020). However, the causal mapping technique (a technique using cognitive maps to reflect potential causal relationships between the elements of the map and their strength, in other words, causal maps) focuses on assessing students' insights into the underlying causal mechanisms of the topic. The causal maps are used to formally represent students' cognitive structures and capture them in various stages of the learning process — particularly at its beginning and end. As such development (change) of the formalized structures representing the students' understanding of the key concepts and their relationships can be analyzed, and learning can be operationalized in many ways — as a change in these structures, their configuration, complexity, reasonability, consistency, etc. This approach allows for the dynamic and unsupervised assessment of learning outcomes. Dynamic because the change (or lack thereof) in the cognitive structures is being investigated, and unsupervised because the differences in the cognitive maps are considered to be the outcome of learning and no "correct understanding" needs to be specified beforehand.

1.1. Motivation

Assessment of learning outcomes is an essential aspect of education research, delivering insights into the usefulness of the instructional approaches and the overall influence on the development of the student's knowledge and learning. The learning outcomes describe the knowledge (what the individual knows and understands) and competence and skills (what he/she can do) after the learning (Lile & Bran, 2014). Given this, it has always been a challenge to determine how learning happens and what are its particular effects in a specific context (Veríssimo et al., 2017), particularly in complex areas where the (expert) knowledge requires a deeper understanding of concepts and connectivities (Jones et al., 2014). This motivates us to focus on developing reliable and practical techniques in this study to assess the learning outcomes considering not only at an individual level but also at a group-level.

In the existing research, ability tests, pre-/post-test surveys, questionnaires, and interviews have been frequently used approaches to evaluate the learning outcomes (Jones et al., 2014; Lile & Bran, 2014).

Table 1
Comparison of previous research utilizing causal maps for the assessment of learning outcomes and the approach suggested in this paper.

	Jones et al. (2014)	Veríssimo et al. (2017)	Our work (this paper)
Subject/process that was the focus of the research	Ethical reasoning knowledge assessment	Assessment of learning in mathematics (geometry); management of teaching	Development of methods for the assessments of learning outcomes in general (unsupervised). Strategic decision-making case study.
Supervised/unsupervised assessment	Unsupervised combined with qualitative	Unsupervised combined with Supervised: pre-test used to decide what relations to reinforce and what to weaken (unsupervised) post-test used for supervised assessment	Unsupervised, but allowing for identification of desirable/undesirable effects
Use of tool for mapping	No	Yes	No (not relevant - methods paper)
Pre-/post-test included	Yes	Yes	Yes
Learning (outcomes thereof) operationalized as	Number of correct/incorrect concepts and relationships, and effectiveness of the visualization	Number of correct/incorrect relationships between concepts	Differences in causal maps,[a] Differences in cognitive diversity[b]; Individual and group level considered[c]
Measures/techniques applied as quantitative measures	Map score, SOLO score, Paired sample t-test, Correlation coefficients	McNemar Test	Distance ratios, fsQCA methods, histograms, frequency analysis

[a]This involves emergence, persistence and disappearance of causal relationships, differences in directions and strengths of causal relationships, differences in the sets of strategic concepts (nodes) of causal maps.

[b]Differences between individual beginning and end causal maps, differences between the individual and group causal map in the beginning and in the end.

[c]Analysis can be performed on individual level (individual learning) or group level (group-level learning).

Defining what is correct/incorrect and guiding throughout the assessment process are common properties of such methods. This type of assessment is normative and can also be referred to as supervised assessment. Even though most studies mainly used supervised assessment methods, there are clear indications that these methods are not applicable in all contexts and that some insights cannot be gained using these methods. This implies a need for alternative – unsupervised – methods for the assessment of learning outcomes, that would be able to register a broader range of potential effects of the teaching–learning intervention. However, the focus on unsupervised assessment of the outcomes of learning, and thus of the development of expert knowledge, has been limited so far. Given this, our proposed approach incorporates unsupervised assessment to evaluate the outcomes of learning. Note that a more detailed explanation of supervised and unsupervised assessment types in the context of learning outcomes assessment is presented in Section 3. Unlike other papers utilizing causal maps for the assessment of learning outcomes and/or for the management of the teaching–learning process, we aim to propose a comprehensive causal-map based methodology for unsupervised assessment of the outcomes of learning — see Table 1 for a comparison of the focus of other related studies and this paper.

As an evaluation tool, cognitive mapping has proven to be beneficial for improving and evaluating students' learning performance (Gurupur et al., 2015; Nesbit & Adesope, 2006; Peng et al., 2019; Shen et al., 2019; Wang et al., 2018). The attributes associated with a cognitive map make this tool exceptionally suitable for exploring learning behaviors, particularly from students' perspectives (Hossain & Brooks, 2008). Consequently, an assessment using cognitive mapping intends to examine the causal structure of the learner based on the selection of core concepts, relations among the concepts, and overall organization of their knowledge (Jones et al., 2014). Moreover, when the mapping is used as an assessment to examine a new learning activity, it can exhibit individuals' existing knowledge about the topic/subject focused (Dorough & Rye, 1977). This may support the instructor to organize or update new information. Once it is used at the end of the learning process, the cognitive maps have the potential to reveal both factual knowledge of the subject and acquired knowledge through their own experiences (Jones et al., 2014). In this article, we adopt cognitive maps in the analysis to develop an unsupervised assessment to examine learning outcomes.

1.2. Objectives and research questions

The purpose of the present study is to propose techniques that would allow for the management of the process of expert knowledge enhancement, in other words, for the examination of the changes in students' understanding of the key concepts and their relationships (cognitive structures) in an unsupervised assessment context. The goal is to propose explorative techniques for identifying various effects of a teaching–learning event that would provide clear and actionable insights into what has changed and what has remained the same as a result of learning. We also show and discuss the performance of the proposed techniques in a real CSCL-based course at the university and interpret the identified changes in the cognitive structures of the students (on an individual level and on a (sub)group/class level) in terms of the content of the course. We also point out desirable and undesirable identified effects from the perspective of the intended learning outcomes of the course when possible.

The following research questions have been formulated to guide our research study and help us achieve our desired research objectives. In each question, we focus on the specific aspects (possible results) of the learning process as represented by the below-mentioned features and components of the cognitive maps

(Q1) What are the changes in cognitive diversity within individual and collaborative learning from the start to the end of the teaching–learning process?
The term "cognitive diversity" refers to the different cognitive traits utilized by each student in the learning environment (Shinn & Ofiesh, 2012) as compared to other students or to the "overall" cognitive structure of the group. Each individual has unique cognitive traits, which can be affected and altered when working in a group. In our assessment, students' cognitive diversity within the learning groups is quantitatively assessed using an average distance ratio (Langfield-Smith & Wirth, 1992) between individual and group-level cognitive maps. In this case, we assume that the changes in these distance ratios from beginning maps to end maps reflect learning effects (see Section 5.2 and Fig. 4). The reduction or increase in the cognitive diversity within (sub)groups of the class is assumed to be a direct effect of teaching. The role of cognitive diversity and its link with the performance of the group/company have been investigated, for example, by Kumbure et al. (2020). As such, the knowledge of the effect of the teaching–learning event on cognitive diversity within (sub)groups of the

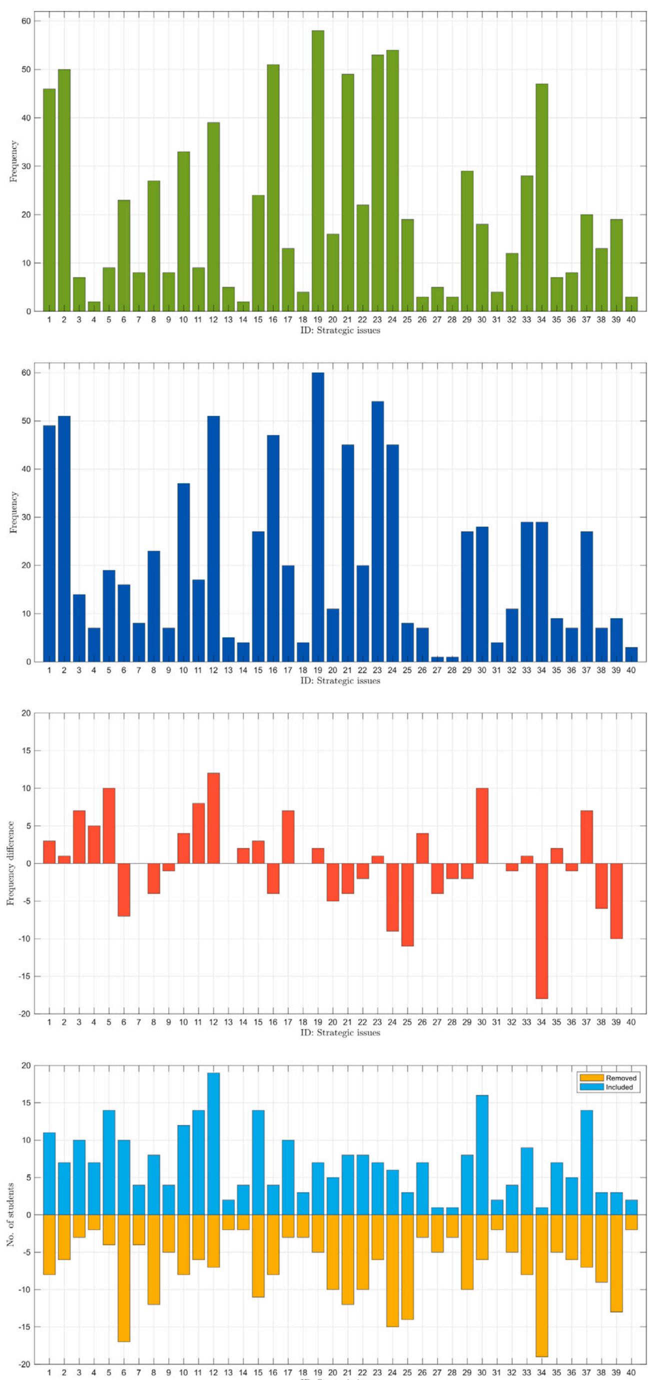

Fig. 1. Frequency values of the strategic issues included in the students' cognitive maps, considering Q2. TCSR (41) is not included as it had to be present in every cognitive map provided by the students. The top sub-figure describes the frequencies of usage of all the strategic issues in the maps provided at the beginning of the course; the second sub-figure the frequencies for the end maps; the third sub-figure summarizes the difference in the total frequency of use of the strategic concepts (positive values mean a larger frequency in the end maps). The final fourth sub-figure provides a more individual-level view of the changes, where all emergences (positive frequencies) and removals (negative frequencies) of the strategic issues are being tracked.

class can be relevant in particular types of courses. We also investigate the individual-level cognitive diversity, that is, the difference between the cognitive structure of an individual and an "overall" (average) cognitive structure of the (sub)group the individual is a member of and its development as a result of learning (see Fig. 5).

(Q2) What is the change in the perceived importance of the strategic issues (nodes)?
This is reflected in the selection of the strategic issues to be included in the individual cognitive maps produced at the beginning and at the end of the teaching–learning event. The investigation of this aspect (see Fig. 1) can show which strategic issues (modeled by nodes in the cognitive maps) are considered important/relevant at the beginning of the event and how they are replaced by others as an effect of the teaching–learning event, but also the consistency of the effect of the teaching/learning event in terms of the inclusion/exclusion "traffic" connected with the strategic issues as shown in the last sub-figure of Fig. 1. Appropriate presentation of this issue can show whether the effect of the teaching–learning event is the same for all the students or whether some strategic issues are being newly included by the student in the cognitive maps produced at the end of the course while these very same issues are being replaced and discarded by others.

(Q3) What are the changes in the causal relationships among the chosen strategic issues in the cognitive structures of the students (represented by individual-level causal maps)? In this context, we investigate the following effects of the teaching–learning event:

- *The appearance of new causal relationships* — this can be understood as a realization of the existence of relationship as a result of learning and its inclusion in ones cognitive structure (see Fig. 8 and Table 6 that summarize the results of the analysis concerning the emergence of new causal relationships on a group (course overall) level). The reasonability of the frequently emerging causal relationships can be assessed afterward. Attention should also be paid to the emergence of not-so-reasonable or difficult-to-justify causal relationships as well as of those that would directly contradict the theoretical framework of the teaching event. If such "undesirable" causal relationships are emerging, the teaching/learning event structure, form, and content should be revised in order to avoid misunderstandings, the creation of misconceptions, and undesirable relationships in the cognitive structures of the students. Also, the number of causal relationships that are added by the individual students as a result of learning (see Fig. 9) can be of significance, and therefore, this is also investigated.
- *The disappearance of causal relationship* — this can indicate that a given causal relationship is no longer considered valid as a result of the teaching–learning event or that the respective strategic issues are not assigned sufficient importance to be kept in the cognitive structure (causal map). The interpretation of the information obtained in this phase (see, e.g., Fig. 6 or Table 5) aims at the qualitative assessment of the relationships that were removed. The disappearance of a reasonable and important causal relationship can be considered a problem, whereas the disappearance of irrelevant or directly undesirable (incorrect or unjustified) causal relationships represents a desired effect of the teaching–learning event as it means a simplification of a cognitive structure or its improvement towards a more correct one respectively. Also, here the number of causal relationships that were removed in individual causal maps (cognitive structures) can be relevant for the understanding of the effects of the learning event (see Fig. 7).

- *The persistence of causal relationships* — in other words, the identification of those relationships in the cognitive structures that are present at the beginning of the learning event and remain present at its end (see Fig. 11 or Table 10). These relationships can be considered unaffected by the teaching–learning event or confirmed by the event. The persistence of "undesirable" or "incorrect" relationships might point to a need to adjust the focus of the teaching event or the need to pay attention to the correction of these misconceptions during the teaching process more. The persistence of desirable (correct) relationships, on the other hand, is a bit more difficult to attribute. At the very least, we can say that the teaching–learning process did not distort these desirable/correct relationships in the cognitive structures of the students. Table 11 shows individual-level results for the most robust causal relationships.
- *The changes in the perceived strengths of the causal relationships and in the polarity of the causal effects* — to accompany the above-suggested analysis, we need to investigate also the relationships that are persistent in the cognitive structures of the students, but whose strength of the causal relationship (or even the polarity of this relationship) changes. The changes in the perceived causal strengths of persistent causal relationships are more subtle effects of learning but might still provide interesting insights into the effects of the teaching–learning process (see Fig. 10). The changes in the polarity of the causal effects (negative switching to positive, positive to negative, etc.), on the other hand, indicate a stronger influence on the cognitive structures that can, again, be assessed in terms of desirability and reasonability and the teacher can subsequently act upon this information (see Tables 7 and 8). If needed, the analysis of the polarity changes can also be performed on the level of individual causal relationships (see Table 9).

From the teaching perspective, this information obtained from the proposed analysis of the cognitive maps helps the teacher to improve and create targeted tasks by including more relevant features and conditions that strengthen the students' performance, which can facilitate the creation of desirable relationships, the removal of undesirable causal relationships, modification of the direction and polarity of the causal relationships, etc. All this after the analysis of the results of the proposed learning outcomes assessment method and evaluation of the (un)desirability of the identified changes in the cognitive structures. Obviously, the end causal maps can also be compared to the "ideal" causal map representing the correct understanding of the concepts and their relationships, as long as the ideal map is available. This normative aspect of the evaluation of learning outcomes is, however, left out of the scope of the analysis proposed in this paper, as we focus on the explorative unsupervised assessment of learning outcomes here. Additionally, the process can also provide us with critical success factors regarding global market operations from the business point of view.

1.3. Research gap and our contribution

While a considerable amount of research is available to assess the outcomes of the teaching–learning process, there is a significant research gap when it comes to understanding the assessment type applied in the evaluation. Previous studies mainly focused on supervised assessment methods, which involved pre-defining learning characteristics or specific features of pre- and post-assessment method. For example, Samuel et al. (2019) conducted a pre-/post-test assessment based on multiple-choice questions to evaluate the learning outcomes. This study follows a supervised assessment approach by utilizing predefined questionnaires provided to individuals at the beginning and end of the training/course to assess their knowledge development. As an additional example, a study by Curran et al. (2006) performed a study investigating the impact of a web-based continuing medical education program on students' knowledge change and learning outcomes. This study employed pre- and post-knowledge tests as well as skill ability surveys to evaluate the effect of course-offering method. Even though supervised assessments can be straightforward and efficient, they possess specific weaknesses. One such weakness is the requirement to pre-define the key features of correct understanding at the end of the learning process. This can sometimes influence the learning process and introduce biases. Our study aims to address this issue by focusing on developing techniques to assess the knowledge development in an unsupervised form and thus to cover as many potential effects of the teaching–learning process as possible to be able to optimize the expert knowledge enhancement process.

Furthermore, applications of cognitive maps in the research on methodological assessments to understand students' learning patterns and how their perceptions change as an effect of learning remain limited. This clearly shows a need to develop better methods for the assessment of learning, particularly dynamic explorative ones, in other words, methods for the unsupervised assessment of learning outcomes. Also, in the existing literature, while some of the research has studied changes in causal structures in terms of the inclusion/exclusion of correct concepts and the number of changes of associations among the concepts (see e.g., Jones et al. (2014), Veríssimo et al. (2017) and Table 1), no one has explicitly investigated appearance/disappearance of cause–effect relationships from the beginning to end maps. Given this, our research focuses on examining the appearance and disappearance of causal relationships and quantitatively measures the difference between cognitive maps produced before and after the learning. This approach allows us to gain valuable and various insights into the underlying changes in the cognitive maps and the cognitive structures (expert knowledge) they represent. As is apparent from Table 1, previous research on the use of cognitive maps in the assessment of outcomes of learning was heavily dependent on the chosen application and as such the results and methods proposed remain strongly case-dependent. A comprehensive methodology that would propose and analyze the general use of cognitive maps in unsupervised assessment of the outcomes of learning is not available. This paper therefore takes the methodological standpoint and proposes a wide range of method to be used in connection with cognitive maps to assess the outcomes of the learning process in the explorative unsupervised way.

Overall, our research seeks to contribute to the existing literature by addressing the methodological research gap concerning the evaluation of the learning outcomes with an unsupervised assessment, adopting a cognitive map-based approach to examine their development/modification before and after the learning event occurs. The significant contributions of this research are outlined in the following.

- We propose a novel and unsupervised assessment approach that utilizes cognitive maps to systematically examine the development of expert knowledge.
- The proposed approach involves examining the changes in cognitive diversity, causal relationships, and the perceived importance of the elements used in the maps.
- We use real-world data of cognitive maps collected through a strategic decision-making process in a computer-assisted collaborative learning environment to validate the viability and effectiveness of the proposed approach.
- We also discuss the potential value and application of the findings obtained through the proposed method to facilitate the expert knowledge enhancement process.

To the best of our knowledge, this paper is the first study to examine the appearance and disappearance as well as the changes of strength values of causal relationships in the maps to evaluate knowledge developments. In addition, our proposed approach incorporates evaluation techniques such as distance ratio measures (Langfield-Smith & Wirth, 1992), histogram frequencies, and fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 2000, 2008), which is a unique contribution not previously explored. Focusing on the data-drivel exploration, we empirically collect data through a cognitive mapping task to demonstrate the performance of our proposed learning outcomes assessment approach. Students in management teams performed this task within a strategic decision-making simulation in a CSCL environment. The simulation process is performed as a part of a graduate course in business at a university in Finland, and it is designed to assess how well students perceive new concepts and contents. More specifically, during the simulation task, the students receive guidance in which they are taught how to succeed in the business process with international trading strategies in a global market. For the analysis process, we employ specific methods and measures (distance ratio measures and fsQCA methods) used in previous studies (Kumbure et al., 2020; Langfield-Smith & Wirth, 1992; Ragin, 2008), but apply them in unique ways to get insights on the outcomes of the learning process both on the individual and also the group level.

In the analysis, we aim to determine answers to the research questions and hypotheses (that are developed as a specific case) according to two following major expectations: first, we expect that cognitive diversity within a group has changed from the start to the end as an effect of learning; second, we expect that empirical study provides evidence for a significant difference in students' understanding of the key concepts and their relationships between the beginning and end of the CSCL simulation-based course. These changes are expected to be reflected in the structure of the cognitive maps used to represent the students' understanding of the key concepts and their mutual relationships between the beginning and end of the course, namely in the selection of strategic issues to be used in the maps, in the number, strength, and stability of the causal relationships among these issues and also in the changes of directions of these causal relationships. All this will be investigated from the perspective of the individuals, the groups/teams, and the whole set of participants in the course, where applicable.

2. Related works

2.1. Causal mapping in the student learning perspective

Drawing causal maps supports learning by pushing students to think what the essential concepts and their relationships are already when they start the course. Causal mapping hence helps the students to concentrate on thinking what is their pre-understanding of the knowledge domain of the course content (Shen et al., 2019). When constructing causal maps, students must think topics by using conceptualization and the method also directs thinking about relationships between factors. This understanding is then presented in the conceptualized and structured form as a causal (cognitive) map. Constructing the causal maps at the end can visualize and formalize the post-understanding of key concepts and their relationships — the state of understanding with which the student leaves the course or CSCL event.

Many studies have already shown positive effects of adopting cognitive maps on advancing students' subject-related knowledge (Eggert et al., 2017; Nesbit & Adesope, 2006), problem-solving performance (Asiksoy, 2019; Wang et al., 2018), motivation to learn in complex situations (Wang et al., 2018), collaborative learning (Kinchin & Hay, 2005; Sizmur & Osborne, 1997; Wang et al., 2017), programming performance (Peng et al., 2019), and divergent thinking for creativity development (Chen et al., 2021; Sun et al., 2019). In addition, a study by Dhindsa et al. (2011) reported that a constructivist-visual mind mapping-based teaching approach outperformed a traditional teaching approach in terms of enriching students' understanding in a classroom environment, particularly for more complex content. Similarly, Wu et al. (2016) investigated the influence of a cognitive mapping approach on supporting the students in learning the clinical reasoning process effectively. The findings of this study showed a clear advantage of the computer-based cognitive mapping approach compared to the verbal-text method in enhancing the reasoning performance of medical students. Focusing on the teacher's role, Coleman (2014) presented a cognitive map that characterized the teacher's practical knowledge and experience for instructing the students and creating valuable discussions during a class activity. Furthermore, Shen et al. (2019) introduced a different approach based on the mental structures and cognitive maps to identify students' challenges in learning a course and proved that the proposed concept-mapping approach has the potential to support the teachers in understanding the student's learning challenges and improve the teaching efficacy.

From the learning assessment perspective, Jones et al. (2014) illustrated the use of cognitive maps as an assessment tool in examining the learning outcomes and the development of ethical reasoning knowledge of physiotherapy students. Instead of accounting for structural changes directly, this study considered "map scoring" as the evaluation tool in the assessment to examine the improvement of the students' ethical knowledge. Veríssimo et al. (2017) investigated the changes in students' cognitive structures in terms of the relationships between concepts at the individual level after the learning process in Mathematics, particularly geometry. They used causal structures produced by grade nine students using the GOLUCA software in the experiment and analyzed the number of relations before and after the learning process. The results showed significant differences between students' start and end cognitive structures and confirmed the effectiveness of cognitive structures in evaluating student learning. However, this study has only focused on the number of changes in the connections between concepts from pre-test to post-test and has not used the strength values in the cognitive structures. Also, there is no examination of cause–effect relationships in both studies mentioned above.

In the present study, we introduce a new way of using cognitive maps to assess not only students' learning performance but the outcomes of learning as such by investigating the changes in students' cognitive structures as an effect of learning. Various types of changes (changes in the structure of the cognitive maps, in the strengths and directions of the causal relationships, in the cognitive diversity, etc., are being studied, even the absence of changes) are investigated and analyzed from different perspectives. Notably, this research extends the knowledge in the context of individual learning and collaborative learning through the assessments not only of students' learning patterns at the individual level but also of their learning performance at the group level in the CSCL framework. In particular, an unsupervised approach to assessing the learning outcomes, which allows for identifying the actual effects of a teaching event on the students, is proposed. To our knowledge, no one has attempted to study the teaching–learning process by using students' cognitive structures in the context of unsupervised learning assessment to this extent so far.

2.2. Variability in students' perceptions in learning

While considering cognitive mapping as the primary methodological aspect, the change of students' cognitive structures in the learning process is the key focus of our study. Examining all possible measures regarding the educational setting is crucial in advancing the quality of teaching activity and students' learning performance (Roff, 2005). The most used and effective way of investigating such measures is to evaluate the effects of the learning process on students' in a given educational context (Bakhshialiabad et al., 2015). Accordingly, it is evident from the previous studies that students' perceptions, understanding of the key concepts and their relationships, and their variations have significant impacts from teaching strategies (Cho et al., 2021), learning environment (Bakhshialiabad et al., 2015; Shrestha et al., 2019), teacher's support and perceptions (Pietarinen et al., 2021), teamwork (Hadwin et al., 2018), and collaborative discussions (Leinonen et al., 2003), to mention a few.

Based on the empirical findings reported in the literature, students' perceptional changes can be seen as positive results in the learning process. In fact, we assume that a deep understanding of the variability of students' perceptions of learning can be beneficial for the coordination of the teaching activity and for the allocation of resources in an efficient way. Essentially, knowing to what extent students change their cognitive structures as an effect of learning makes the process more straightforward. This variability of students' perceptions can be defined by focusing on the different levels (e.g., low, medium, and high) of changes or what context is included in the changes in terms of concepts, effects, complexity, etc. Another thing is that it is also necessary to have a valid, reliable, and effective tool to evaluate such perceptional changes. Given this, the concept of cognitive mapping is probably the most promising due to its topological structure that can be further computed and the ability to represent human cognition in various ways. We, therefore, essentially focus on examining the variability of individual and group-level cognitive structures during academic work through cognitive mapping-based assessments. According to Norman and Gentner (1987), reorientation of cognitive structures in terms of the used concepts and relations can be understood as a creation of new knowledge. In light of this, we seek to investigate the students' learning performance and causal changes by comparing the beginning and end cognitive maps.

3. Assessment types of learning outcomes

In an analogy to computer science, one can distinguish two possible types of assessment of learning outcomes:

- *supervised assessment of learning* that operates with the concept of "correct" or "desirable" knowledge (abbreviated as "correct understanding" further in the text), where the knowledge, skills, cognitive structures, etc. of the students are compared to this correct understanding and deviations from the correct understanding are considered undesirable and are to be eliminated. This approach to the assessment of the outcomes of learning can be efficient and provide useful insights for the management and optimization of the teaching/learning process. However, it frequently also comes with the necessary requirement of specifying the key features of the correct understanding and, therefore, with the need to focus on pre-defined aspects of the learning or specific parts of the cognitive structures of the students. And these need to be specified by the person designing or carrying out the assessment. To represent this type of learning outcome assessment, we can formulate its goal as *"Let us see if you understand it correctly."* This type of evaluation can thus be understood as normative. The correct/incorrect continuum is a useful one to guide the learning process, and it can also provide some insights needed for the management of the teaching process. Unfortunately, the need to specify what is (in)correct in advance can lead to some effects of the learning process escaping the teacher's/instructor's attention.
- *unsupervised assessment of learning* that can be represented by the goal *"Let us see what you have learned."* It is clear that this approach is less suitable for the direct assessment of the correctness of the outcomes of learning, as it does not directly provide the answer whether the obtained knowledge, skills, understanding, etc. is correct. On the other hand, it is capable of describing what has changed as a result of the learning process and as such it can be very valuable in the guidance and planning of the learning process. It allows for a complex assessment of the process of learning that can be fully exploited for the management and optimization of the process of teaching. This approach to the assessment of learning outcomes is more explorative than normative and aims on mapping the effects of the teaching/learning process in their entirety. It is also more dynamic than static, as it focuses on what has changed as a result of the teaching event.

In essence, both the above-mentioned types of evaluation require the assessment of the "final state" of the skill, cognitive structure, understanding, etc., as it manifests itself after the learning/teaching process. For the normative (supervised) assessment, it can be enough to check the state after the learning/teaching process takes place only. In other words, it might be enough to assess the (in)correctness of the understanding, (in)sufficiency of the skill, etc. This might be the reason why the outcomes of learning are frequently assessed this way. Another reason for the frequent use of the supervised assessment methods might be the above-mentioned relevance to the management of the learning process and its seeming simplicity - a single "measurement" is done at the end of teaching/learning and correctness or appropriateness of the resulting skill, cognitive structure or understanding is checked and quantified, if needed. If the assessment of the learning outcomes is done only at the end of the learning/teaching process, then the assessment can be considered static.

The explorative unsupervised assessment of learning requires the knowledge of the "starting state" as well. In other words, if we want to see what has changed as the result of the learning/teaching process in the cognitive structures of the students, we need to know how they looked like prior to the teaching event and how they look like when the teaching event has ended. This requires an additional measurement of the baseline level of knowledge/skill/understanding at the beginning, which is more tedious and resource-intensive. The potential benefit is analogous to the benefits of other explorative methods — it is possible to gain more insights into the effects of teaching, analyze them and perform corrections of the process if needed. In other words, we can obtain valuable insights concerning the effects of the teaching action that might have been overlooked by the normative supervised assessment method. Even the desirability of the identified changes (or the absence of a change in a specific area) can be established ex-post. The difference from the supervised assessment of learning is that we do not specify what to consider and what to check for correctness. On the contrary, we can identify notable changes in the cognitive structures or their rigidities in all their variability, assess their desirability and act upon this information. Table 2 summarizes the main features of supervised and unsupervised techniques to assess learning outcomes.

It is also interesting to note that if the baseline measurement is not performed in the beginning, the normative supervised assessment of the outcomes of learning might not be informative of the effects of teaching at all. Consider a situation when the correct understanding was present prior to the teaching event, then its presence at the end of the event does not signify the efficiency of the teaching event, it just shows that the teaching event did not distort the correct understanding with the particular individual. In other words, no-effect might not be distinguishable from a desirable change in the cognitive structure or even from an undesirable change in the cognitive structure. Still, if the final state of the cognitive structure (skill, understanding, etc.) is of importance, then the normative assessment can serve its purpose well. But if the teaching/learning process is to be optimized, then the baseline measurement is also needed for the normative assessment (to be able to attribute the change to the teaching action) and thus, the normative assessment loses a part of its "simplicity advantage" over the unsupervised learning.

4. Materials and methods used

In this section, we first conceptualize the context of the study, participants, and data collection of cognitive maps along with the students' computer-supported collaborative learning simulation task used to show the performance of the methods proposed in this study. This is followed by introducing the measures used, including distance ratios and fuzzy set-theoretic measures.

Table 2
Comparison of main features of supervised and unsupervised techniques for the assessment of learning outcomes — a summary.

Goal	Supervised assessment of learning outcomes	Unsupervised assessment of learning outcomes using causal maps
Identification of "correct" and "incorrect" cognitive structure and its elements	Yes, with respect to a given "correct" knowledge representation	Yes, desirability of each effect of learning can be assessed separately, "correct" knowledge representation can also be utilized
Ability to assess difference from "correct" knowledge (if known)	Yes	Yes
Effects covered	Static, usually only final state measured, no means of attributing the "success" to the teaching–learning intervention	Dynamic (as a difference of two static captures of the cognitive structure in different times) Changes between start and end representation of expert knowledge can be attributed to learning
Identification of persistent relationships between concepts (unaffected by the teaching–learning intervention)	Difficult (due to static nature). Also potentially limited by the focus on the "correct" knowledge.	Yes, persistent relationships can be identified, their desirability can be established after their identification.
Needed number of assessments	At least 1 (usually after the teaching–learning event)	At least 2 (at the beginning of the teaching–learning event and after its end)
Main focus on	Differences from "correct" knowledge and its formal representation.	Differences between the start and end knowledge and their representations.
Limitation of use	Not applicable where "correct" knowledge is difficult to define (e.g., ethics)	Not well suited for simple fact-checking (factual knowledge not representable by a causal map)

4.1. Context of the methods' applicability study and participants

Examining the variability in students' learning needs a research context that allows studying the same students in different settings. These settings should vary so that they stimulate different levels of surface and deep learning (Nijhuis et al., 2008). The present study was based on a course held for two periods (14 weeks) in a year at the business school at a university in Finland. This CSCL course aims to familiarize students with strategic planning for international business in general and the management and execution of global business strategies within the context of multinational corporations in particular. The general idea of this course is to support the students in understanding various international or global strategies and their advantages and disadvantages.

A total of 71 master's degree students[1] participated in the course during the selected academic year, and they were supposed to have prior knowledge of international business to start this course. At the beginning of the course, the students were instructed to visualize their cognitive structures concerning the possible effects (direct and indirect) of chosen 12 strategic issues considered by them as the most relevant ones on the total cumulative shareholder returns of a company. This way, the beginning causal maps were produced for the participants of the course. During the course, students were required to perform an eight-week business simulation task on strategy implementation in a controlled setting, which aimed to expose the students to actual management challenges in an international context. Subsequently, two to five students, working as a team, shared their cognition, interpretations, and opinions during the simulation exercise. Throughout the simulation task, the teacher instructed and supervised the students to understand and interpret the operations of international trading strategies in global business in a dynamic and competitive environment. After the simulation was concluded, the cognitive structures of the students were captured again using the cognitive maps. The performance of teams in the simulation task was measured by the total cumulative shareholder returns (TCSR), defined as the average percentage return that shareholders receive annually from the company during the entire simulation.

[1] This is the number of students who completed the course.

4.2. Applicability study data collection — cognitive map creation and formal representation

In the data collection, there were 71 individual-level cognitive maps originally belonging to 16 management teams consisting of students in the simulation, created based on 40 strategic-level constructs presented in Table 3. As explained in the previous subsection, the data samples of individual cognitive maps were collected two times, (i) at the beginning and (ii) at the end of the simulation task. To create a cognitive map, each individual selected 12 constructs (from the list in Table 3) perceived as the most relevant from his/her knowledge and unique views on the situation. Each cognitive map also included the TCSR, as the causation of TCSR was the main point of investigation in the course/simulation. Regarding the student simulation task, the share price for each group was the same at the beginning of the simulation task. However, it changed over the simulation process according to the success of the groups in the decision-making process. Moreover, it was not allowed for the groups to issue new shares or repurchase existing shares during the simulation.

For the purpose of this study, we intended to examine the cognitive diversity between the start and end cognitive maps as well as the changes in the structure and content of the maps at the individual- and group levels. To do so, that is to allow for formal calculations and automation of the analysis, we first converted all individual cognitive maps into adjacency matrices. To simplify the analysis, a 41×41 adjacency matrix represented each individual map (i.e., the 40 strategic-level constructs plus the TCSR defined each matrix dimension). Each cell value of the matrix represents the strength (weight) of the causal relationship between two elements in the cognitive maps (the corresponding row element is then considered to be the cause for the corresponding column element). The strengths of these causal relationships were chosen from the vector $(-3, -2, -1, 0, 1, 2, 3)$, where the sign reflects the polarity of the relationship and 0 would represent a nonexistent causal relationship (see, for example, Table A.1 in the Appendix). It is also worth mentioning here that an adjacency matrix corresponding to a cognitive map of an individual is referred to as an individual map. In particular, an average adjacency matrix for all individual maps in a group represents a group-level map.

Fig. 1 displays the frequencies of the strategic topics that appeared in the individual starting and end cognitive maps in the original data. In addition, frequency differences between the end and starting maps are also demonstrated. With this result, we attempt to answer Q2. The information in the figure allows us to understand which strategic issues

Table 3
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		

have/have not gained more attention during the students' decision-making process within the simulation task. For example, one can see from the top sub-figure in Fig. 1 that "Sales" (19), "Growth of the company" (24), "Long-term profitability" (23), "Dividends" (16), and "Demand" (2) were the most frequently (≥50) used variables before the actual business simulation process. Besides, some strategic issues such as "Contract manufacturing" (4) and "Transfer prices" (14) have received limited attention from the students. Frequency differences (see the third sub-figure in Fig. 1) also give a clear view of these changes on a group level. However, notice that Fig. 1 demonstrates the frequency rate of the strategic issues used by students and does not indicate any influences of them. Additionally, the frequency difference sub-figure of Fig. 1 (the third from the top) only provides an aggregated view of the changes in the frequency of use of the key concepts in the maps. A more detailed plot that summarizes the "change traffic" on a more individual level is presented in the bottom sub-figure of Fig. 1. The bottom sub-figure in Fig. 1 can be used to better understand the effect of the CSCL event in terms of the perceived importance of the strategic issues. It is possible to see the potentially ambivalent effect of the teaching event, where some strategic issues are discarded by some students as a result of the event, while for others, the same strategic issues emerge in the end maps. The knowledge of strategic issues that seem to be the most reconsidered ones can help the teacher in the design and targeting of the CSCL course in the future.

By looking at the frequency differences in Fig. 1, where the third sub-plot represents the differences in frequencies of use of the strategic issues at the beginning and end causal maps on the overall course level, we can see that some of the concepts appear or disappear from students' cognitive maps during the course. For example, the frequency for concepts such as "Mission and vision" (29), "Supplier selection" (39), and "Interest rates" (32) clearly decreases during the course, whereas the frequency for concepts such as "Product selling prices" (12), "Equity ratio" (37), and make or buy decisions on manufacturing [i.e., "Own manufacturing" (3), and "Contract manufacturing" (4)], increases during the course. One interpretation of this is that at the beginning of the course, concepts in students' causal maps tend to be more abstract (e.g., "Mission and vision" and "Supplier selection") or externally given (such as "Interest rates"), but during the course, they convert into concepts that are more concretely related to own decision-making.

In our data collection, the cognitive maps have been drawn by the students to evaluate the impacts of the chosen 12 strategic topics on each other and the TCSR during the business simulation task. Therefore, the nodes in the cognitive maps represent those strategic issues and the TCSR, while directional edges with strength values represent the causal effect relations between the two nodes. A causal effect could be negative (−) or positive (+), and its weight might be weak (one), moderate (two), or strong (three) (Hodgkinson et al., 2004). Fig. 2 illustrates an example of the cognitive maps in the original data of this study, including positive and negative causal relationships between the elements with associated weights.

4.3. Distance ratio measures used for analyzing cognitive maps

To analyze and compare the cognitive maps, several quantitative measures have been developed in previous research. As one of them, the distance ratio (DR) (Langfield-Smith & Wirth, 1992) is a well-known method to measure the difference between any pair of cognitive maps. It is a value between 0 and 1, and when DR is 0, the maps are identical, and when DR is 1, the distance between the maps is at its maximum (Markoczy & Goldberg, 1995). In this research, we employed two distance measures: the first measure initially presented by Langfield-Smith and Wirth (1992, Eq. (12)) can be defined as follows:

$$DR_1(A,B) = \frac{\sum_{i=1}^{p}\sum_{j=1}^{p} \mid a_{ij}^* - b_{ij}^* \mid}{6p_c^2 + 2p_c(p_{u_1}+p_{u_2}) + p_{u_1}^2 + p_{u_2}^2 - (6p_c + p_{u_1} + p_{u_2})} \tag{1}$$

where

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

and A and B are two cognitive maps represented by their adjacency 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 ith row and jth column in the adjacency matrices relative to map A and B, respectively.

Secondly, we also employed a novel distance ratio measure that was recently introduced by Bergman et al. (2020) as an enhancement of the one presented by Eq. (1). The purpose of applying this measure was to gain further support for the examination of cognitive maps. In this generalized version, unit area information is considered, meaning that the non-zero elements in both maps are taken into account. The formula

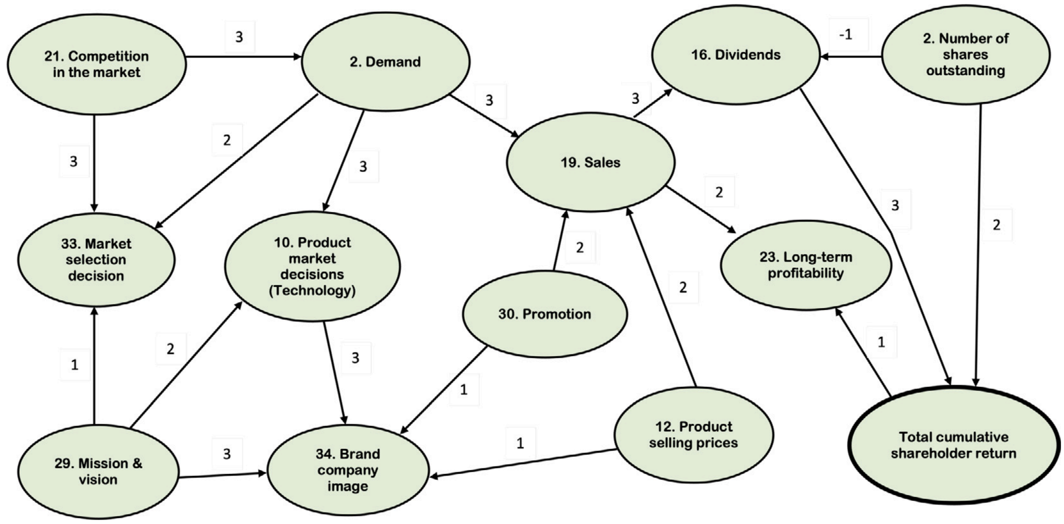

Fig. 2. An example of a cognitive map in our data collection — as provided by the individuals during the business simulation activity.

of this measure can be presented as follows:

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

where A_a and B_a are the count of causal relationships included in the cognitive map A and B, respectively and $T_2 = \max([A_a, B_a])$.

4.4. Set-theoretic consistency and coverage measures

In this research, one focus of our analytic approach is based on the fuzzy set-theoretic qualitative comparative analysis (fsQCA). This approach is particularly applied here for the investigation of the changes in polarities and magnitudes of causal relationships. The fsQCA that was initially defined by Ragin (2008) is a powerful method that allows us to interpret causal (cause–effect) relationships between predictor and outcome by identifying which conditions are necessary or sufficient to produce the outcome (Skaaning, 2011). This study mainly focuses on two essential notions in the fsQCA: consistency and coverage, which can be formally defined in the following way.

Let us consider two features $\mathcal{A}$ and $\mathcal{B}$ in a set X of observations available such that $\mathcal{A} \sim A \subseteq X$ and $\mathcal{B} \sim B \subseteq X$, in which A and B are two subsets of observations in X as they can represent the features $\mathcal{A}$ and $\mathcal{B}$, respectively. Alternatively, we can also allow for the observations to have the features only partially, in which case A and B would be fuzzy subsets of X, in other words, $A \subseteq_F X$ or $B \subseteq_F X$, where for any $x \in X$, we can denote the membership degree of x to A as $A(x) \in [0,1]$ and its membership degree to B as $B(x) \in [0,1]$. The value $A(x)$ then represents the degree to which x has the feature $\mathcal{A}$, and the interpretation of $B(x)$ is analogous. Suppose that now we want to investigate whether the feature $\mathcal{A}$ could be a necessary or sufficient condition of the feature $\mathcal{B}$ also being present in the given observation. To achieve this, we can consider a relationship $\mathcal{A} \Rightarrow \mathcal{B}$ and examine its correspondence with the available data. Put it differently, if we want to find out whether $\mathcal{A}$ is a sufficient condition for $\mathcal{B}$, then we need to focus on the $A \subseteq B$ relationship, and if $\mathcal{A}$ being a necessary condition for $\mathcal{B}$ is of interest then we need to focus on $B \subseteq A$.

Set-theoretic consistency refers to the proportion of cases of $\mathcal{A}$ coinciding with $\mathcal{B}$ in all cases of $\mathcal{A}$ in the data. In other words, it provides a measure of empirical evidence supporting the claim investigated (for example, $A \subseteq B$). 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 $\mathcal{A}$ is not sufficient for the outcome of $\mathcal{B}$ to be present (in other words, there are observations $x \in X$ such that they possess the feature $\mathcal{A}$ but do not have the feature $\mathcal{B}$). Besides, coverage refers to the proportion of the cases of the outcome $\mathcal{B}$ that are associated with $\mathcal{A}$ considering all cases of $\mathcal{B}$ in the data (Kumbure et al., 2020; Schneider & Wagemann, 2012). Coverage often works against the consistency, which means high coverage may have low consistency and vice versa (Kent, 2008). In this research, to compute the consistency and coverage values, we applied the standard formulas presented in Stoklasa et al. (2018) in the following way:

$$Consistency(\mathcal{A} \Rightarrow \mathcal{B}) = \frac{Card(A \cap B)}{Card(A)} = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} A(x_i)} \quad (3)$$

$$Coverage(\mathcal{A} \Rightarrow \mathcal{B}) = \frac{Card(A \cap B)}{Card(B)} = \frac{\sum_{i=1}^{n} \min(A(x_i), B(x_i))}{\sum_{i=1}^{n} B(x_i)} \quad (4)$$

where A and B are two fuzzy sets on X. Here we assume that the cardinality of a fuzzy sets[2] A and B are nonzero, that is $Card(A) = \sum_{x \in X} A(x) \neq 0$ and $Card(B) = \sum_{x \in X} B(x) \neq 0$ with respect to the relationship $A \Rightarrow B$. When $A \cap B = A$, then $Consistency(A \Rightarrow B) = 1$ (perfect consistency), and this implies that there is no evidence that contradicts the given relationship in the data.[3] We can also conclude that $\mathcal{A}$ is a sufficient condition for $\mathcal{B}$. Besides, $Coverage(A \Rightarrow B) = 1$ implies that $A \cap B = B$ and thus we can also conclude that $\mathcal{A}$ is a necessary condition for $\mathcal{B}$. If there are other "causes" for $\mathcal{B}$, 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 $\mathcal{A}$ is the only cause for $\mathcal{B}$, and there are no counterexamples from the data (Stoklasa et al., 2017).

Generally, we prefer to get a good balance from various consistency and coverage ranges for a particular situation. If the relation has very high consistency but a low coverage, that does not describe many cases at all, and the relationship might be too specific, even though rather strong. In contrast, if the relation has very high coverage with low consistency, that indicates a weak relationship because there is no sufficient evidence from the data.

[2] Cardinality of a fuzzy set P on a finite universal set U is $Card(P) = \sum_{x \in U} \mu_P(x)$, and on an infinite universal set U it is $Card(P) = \int_U \mu_P(x)dx$, where $\mu_P(x) : U \to [0,1]$ is called a membership function of P.

[3] 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 $(P \cap Q)(x) = \min\{P(x), Q(x)\}$.

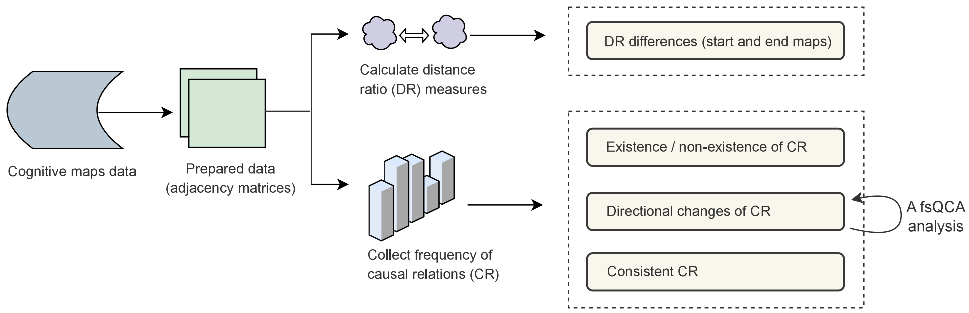

Fig. 3. Flow diagram of the main phases in the research procedure.

5. Proposed approach

By examining strategic interpretations and changes of cognitive diversity in the cognitive maps and changes in their structure and content from start to end, this research aims at investigating the variability of students' perceptions as an effect of learning. Accordingly, several assessments were designed in the research model based on the information extracted from the cognitive maps where the individual perceptions of strategic interpretations have been observed. The steps in the research process and the practical tasks conducted are summarized in the flow diagram presented in Fig. 3. In principle, there were two main assessments in our applicability study on the data from a real-life university-level CSCL course, (i) group-level assessment of learning outcomes using distance ratio measures and (ii) individual-level assessment using the frequency information of causality changes in the causal maps. The steps of these analyses are discussed in detail in the following sub-sections.

5.1. Data preparation

Tackling the quality issues and errors in the data is critical to ensure that early mistakes do not influence the analysis results later. Accordingly, at the beginning of the data analysis in our methods' applicability study, we focused our attention on several issues, such as data entry errors and systematic errors, and the improvement of the quality and reliability of the input data. In addition to that, we noticed that the end cognitive maps of some individuals were not available, even though the starting maps of corresponding individuals existed. In this case, we ignored such starting maps, and the respective individuals were not included in the analysis. Besides, to avoid the issues in matrix calculations, we ensured that all adjacency matrices representing the cognitive maps were in the size of 41×41. In other words, all the adjacency matrices considered all the 41 key concepts listed in Table 3 as potential nodes in the corresponding causal maps.

5.2. Distance ratio-based assessment — analysis of the effects of learning on cognitive diversity

In this assessment, we aim to examine how cognitive diversity within a group has changed as a result of the learning process during the simulation task. To achieve this, we first calculate the distance ratios from the individual-level maps (from those within the group) to the group-level maps considering the whole data sample [i.e., $DR(\text{group}_{i,1}, \text{individual}_{ij,1})$ and $DR(\text{group}_{i,2}, \text{individual}_{ij,2})$, where for group i and its individual j, 1 and 2 denote the beginning and end causal maps, respectively]. Subsequently, we considered the differences in calculated distance ratios (internal diversity) between the end and the beginning for each individual [i.e., $DR(\text{group}_{i,2}, \text{individual}_{ij,2}) - DR(\text{group}_{i,1}, \text{individual}_{ij,1})$] and then averaged those differences at the group level. In this way, we aim to identify changes in the average distance of the individual maps from the group-level map within the given group as an effect of learning during the course. We also investigate the changes in the individual distances from the group-level map as a result of learning. Additionally, it is worth mentioning that both DR_1 and DR_2 measures were used to compute distance ratios for this analysis.

5.3. Analysis of the changes in cognitive structures as an effect of learning

This analysis investigated the changes in the causal relationships in the individual cognitive maps from the beginning of the course to its end, considering Q3. We started this analysis by collecting the frequency of each causal relationship for each strength value going through all adjacency matrices of the cognitive maps. A strength value for a particular causal relationship was allowed to vary from −3 to 3, and it was possible for the same causal relationship to appear in more cognitive maps with different strengths. Each individual cognitive map had to include the TCSR and 12 more selected key concepts from the list presented in Table 3, it was allowed to include as many causal relationships between the pairs of the selected key concepts as needed, no relationship could be included more than once. Each causal map was then represented by a 41×41 adjacency matrix $A_j^k = \{a_{m,n;j}^k\}_{m,n=1}^{41}$ where $k = 1$ indicates a beginning matrix, $k = 2$ indicates an end matrix, $j = 1, \ldots, 71$ is the index of the individual (student) and $a_{m,n;j}^k \in \{-3, -2, -1, 0, 1, 2, 3\}$ represents the strength of the causal relationship between key concepts m (cause) and n (effect) as perceived by the student j; when $a_{m,n;j}^k = 0$ then the causal relationship is not present in the given causal map. In this way, we can now perform the frequency analysis of all the possible causal relationships in the individual maps. For instance, suppose that we have received the frequency vector $(1, 3, 2, 20, 7, 17, 14)$ with the strength vector $(-3, -2, -1, 0, 1, 2, 3)$ for a causal relationship within the starting maps. It indicates that 1 individual weighted this causal relationship (-3), 3 individual weighted (-2), etc., for the causal relationship when the simulation was started. By collecting these frequencies, we can now assess the existence/non-existence, directional changes, and robustness of a given causal relationship from beginning maps to end maps. Subsequently, we attempted to answer the following research questions: the extended questions of the cases discussed under Q3 in Section 1.2, which aim at the understanding (unsupervised assessment) of the outcomes of learning:

- Q3.1 What are the causal relationships that exist in the beginning maps but do not exist in the end maps? This would mean that the students learned that a particular relationship between a pair of strategic concepts has no meaning in terms of a cause–effect relation, even though they originally thought that this relationship was relevant.
- Q3.2 What are the causal relationships that do not exist in the beginning maps but do exist in the end maps? This assessment is analogous to the previous one but identifies those relationships that became relevant as a result of learning.
- Q3.3 What are the causal relationships whose polarity has changed from the beginning to the end of the course? This examines the

Table 4
The hypothesis models in linguistic levels with the strengths at the beginning and the end.

		Causal strengths in the end		
		Negative	Zero	Positive
Causal strengths in the beginning	Negative	H_{01}	H_{04}	H_{07}
	Zero	H_{02}	H_{05}	H_{08}
	Positive	H_{03}	H_{06}	H_{09}

directional changes (up and down) in terms of the positivity and negativity of the causal relationships.

Q3.4 What are the causal relationships that the students expressed at the beginning of the course and that ended up being the same (or close to the same) by the end of the course? This identifies robust relationships present and unaffected by the learning.

The purpose of Q3.1 and Q3.2 was to investigate what kind of causal relationships were excluded or developed during the course. In particular, we examined how strong such a relationship was and how many individuals believed and agreed on this relationship. In principle, these tasks directly track the impact of the course learning on the students' decision-making process during the business simulation activity. The examination associated with Q3.3 intended to explore polarity changes of the relations (+ to −or other the way around) — this would mean that learning manifested itself as a change in the strength of the causality and also in the change of its sign meaning that a strengthening effect turns into weakening one or vice versa. Moreover, Q3.4 regards the idea that either no learning has occurred during the course or the students already knew this in the beginning and believed such by the end of the course. In this way, we analyzed the observed results with Q3.1–4 to describe the characteristics of students' perceived causalities and their diversity caused by the course learning.

5.4. Applying a fsQCA approach

In addition to the frequency-based analysis regarding Q3.3, we further examined how the direction of each causal relationship has changed from the beginning to end in the individual maps as a result of the learning process using a fsQCA approach. Accordingly, we first developed the hypotheses as presented in Table 4, which aimed to detect the changes in causal maps in terms of the strength values. As seen from the table, we specifically considered "zero" (non-existent) the middle point between negative and positive strengths for this analysis and established the hypothesis accordingly. This means, in principle, all causal relationships regarding Q3.1, Q3.2, and Q3.3 were subjected to this fsQCA analysis. Focusing on an example hypothesis in the table, H_{01} implies that the existence of a negative relationship in the beginning map indicates the existence of that relationship at the end as well and the polarity of that particular remaining negative.

The approach used for testing whether a particular hypothesis was rejected or not was based on the context of fuzzification. Fuzzification is a technique applied to transform crisp inputs (exact inputs) into fuzzy inputs to generate the outcomes according to the fuzzy values (Timothy, 2010). In our case, we created the fuzzy sets based on the linguistic labels: negative, zero, and positive. Specifically, we used these labels because the effect of one relationship on another could be negative, positive, or non-existent (zero) in the used cognitive maps data. In this regard, we employed a trapezoidal membership function to calculate membership degrees to the individual frequency results. A general form of the used fuzzy trapezoidal membership function can be defined for a given $x \in U$ (universal set) to fuzzy set P as follows:

$$\mu_A(x) = \Pi(x;\alpha,\beta,\gamma,\delta) = \begin{cases} 0 & \text{if } x < \alpha \text{ or } x > \delta \\ \frac{x-\alpha}{\beta-\alpha} & \text{if } \alpha \le x \le \beta \\ 1 & \text{if } \beta \le x \le \gamma \\ \frac{\delta-x}{\delta-\gamma} & \text{if } \gamma \le x \le \delta \end{cases} \quad (5)$$

where α, β, γ, and δ are real parameters such that $\alpha < \beta < \gamma < \delta$. For this analysis, we categorized membership degrees into negative (−), zero, and positive (+) according to the definitions of the membership functions which can be denoted as $\mu_{-} \sim \Pi(x;\alpha,\alpha,\beta,0)$, $\mu_{zero} \sim \Pi(x;\beta,0,0,\gamma)$, and $\mu_{+} \sim \Pi(x;0,\gamma,\delta,\delta)$, where $\alpha = -3$, $\beta = -1$, $\gamma = 1$, and $\delta = 3$. In this way, we calculated the membership degrees of all observations to the corresponding fuzzy sets representing directional changes of the relations (negative-zero-positive).

Once all membership degrees were obtained, we next calculated consistency and coverage scores to observe all the evidence in favor or against each hypothesis presented in Table 4 (consistency) and also the generality of those hypotheses as evidenced by the data (coverage). In this manner, we employed the fsQCA approach to analyze the change of cognitive diversity at the group level as a result of learning. To evaluate the validity of the hypotheses, we analyzed the consistency values together with coverage values. We prioritized the consistency first during the evaluation and then the coverage scores to obtain additional support for each hypothesis. Regarding consistency, a high value reflects strong support in favor of the evaluated hypothesis. However, depending on the cases we investigated, a specific value required for consistency can also be defined. In this study, we recognized the evidence supporting the hypothesis to be sufficient and reasonable if the corresponding claim has an acceptable consistency value (ranging approximately within $[0.6; 0.75)$), through high (ranging within $[0.75; 0.9)$) to excellent (0.9 and higher), in accordance with the study by Kumbure et al. (2020). On the contrary, we considered that low consistencies do not support the validity of the hypotheses. If the consistency value for a case tested was in the acceptable range or higher, then the coverage value was also considered to determine the validity and generality of the relationship represented by the hypothesis.

All of the computations in this applicability study were implemented using MATLAB 2019b software. In order to compute and store the distance ratio and fsQCA measures,[4] the local functions were generated from scratch. For the rest of the calculations, we used Matlab built-in functions (e.g., to create trapezoidal fuzzy sets).

6. Results and discussion

This section presents and discusses the results obtained during the analysis of the real-life data described before in the proposed methods' applicability study. The investigation was based on two primary analyses, accordingly, the findings of each category are offered under several sub-sections. We first present the distance ratios results obtained with all cognitive maps.

6.1. Distance ratio differences between in beginning maps and end maps (Q1)

As we employed two distance ratio measures, DR_1 and DR_2, to get an unbiased evaluation of the analysis, Fig. 4 displays observed averages of the DR differences at the group level for both measures for all 16 groups. These distance ratios, as stated before, were calculated from the individual maps to the corresponding group map, and then

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

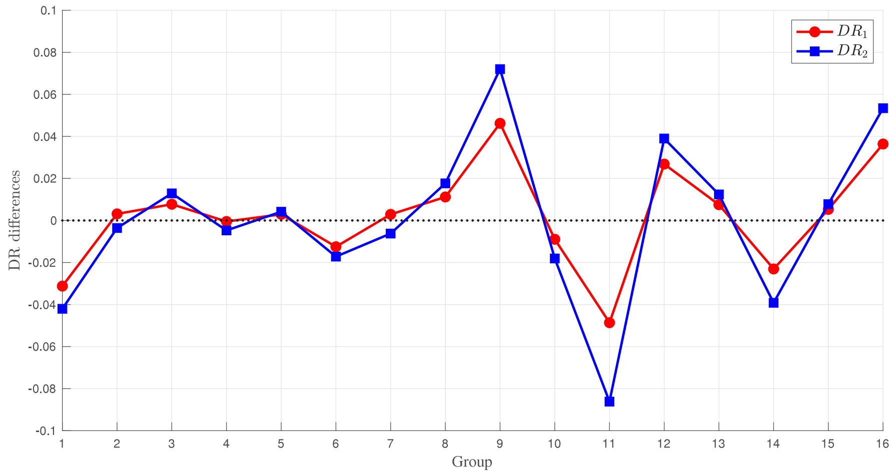

Fig. 4. The variation of DR_1 and DR_2 differences between starting maps and end maps for each group. Negative values correspond with the reduction of the cognitive diversity as a result of learning, positive values correspond with the increase of cognitive diversity within the group.

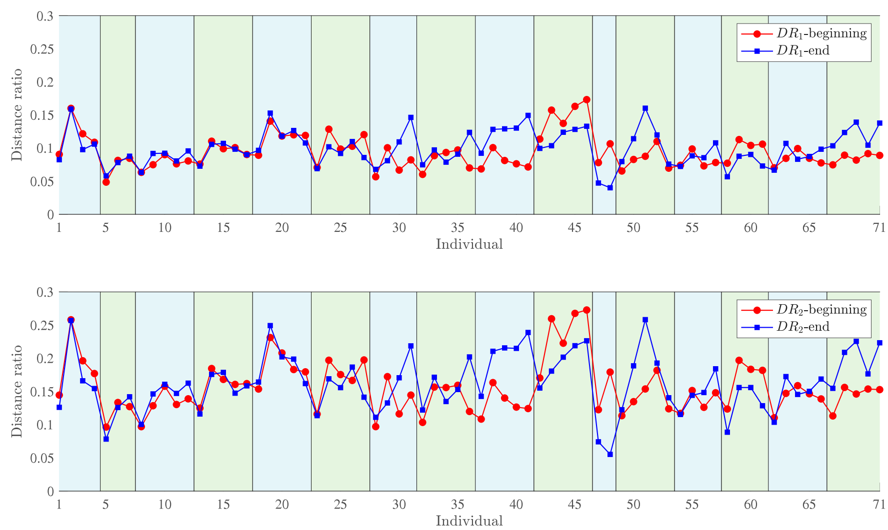

Fig. 5. The variation of DR_1 and DR_2 from individual maps to corresponding group map in the beginning and the end (two different colors separate the groups of individuals from each other).

their differences between the beginning and end were considered. As one can see from Fig. 4, both measures vary in a similar manner around zero, but the DR_2 differences have a slightly higher variation than DR_1.

To get a clear view of the variation of the individual maps within the group from the beginning to the end, Fig. 5 illustrates the distance ratios from each individual map to the corresponding group map regarding the starting and end maps. According to the figure, it is clear that the diversity within the group has always changed from the beginning to the end regarding both distance ratio measures. One can also observe that the lowest end diversity appeared in group "11", in which only two students were included. Looking at Figs. 4 and 5, one can see the effect of learning (of the CSCL simulation-based course) on cognitive diversity at the group and individual levels, respectively. It is, therefore, possible to see whether the teaching leads the students towards consensus in terms of their cognitive structures within their group or whether more diversity is introduced as a result of teaching/learning. Note that even the "individual" analysis, the results of which are presented in Fig. 5, is group-dependent (the distance ratio of the individual map is calculated concerning the group map) and, as such, should not be considered a purely individual assessment of the outcomes of learning.

6.2. Examining the causal relationships that exist in beginning maps but do not exist in ending maps (Q3.1)

This assessment explores 104 causal relationships that showed up in the beginning maps but disappeared in the end maps. For example, Fig. 6 illustrates the frequency distribution of some selected cases, comparing them at the beginning and at the end of the CSCL event. Some of the causal relationships that disappear during the course are not very logical, and therefore the disappearance of such causal relationships is clear evidence of learning (and in case of the disappearance of illogical relationships, the learning can be directly considered correct or desirable). Examples of such relationships are positive impacts of "Market selection decisions" on "Interest rates" (33 ⇒ 32) and "Competition in the market" on "Promotion" (21 ⇒ 30). Some of the disappearing

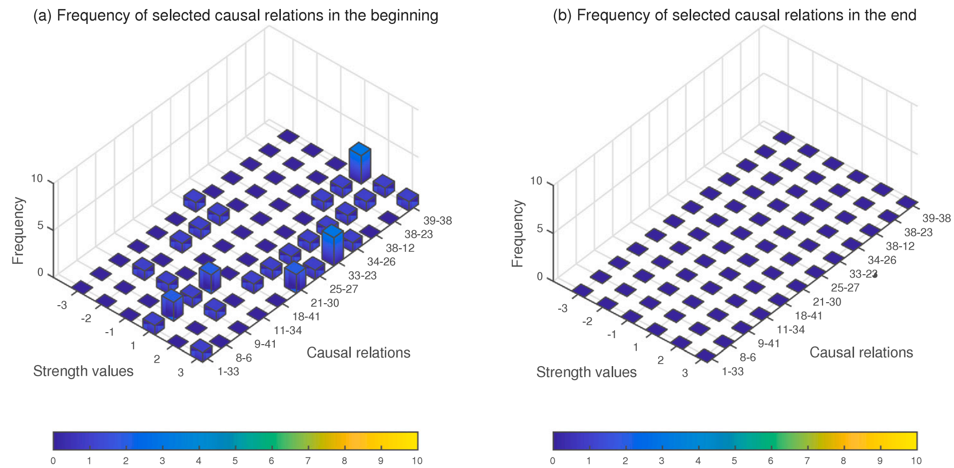

Fig. 6. Some examples of causal relationships that exist in the beginning maps as in (a) but do not exist in the end maps (b).

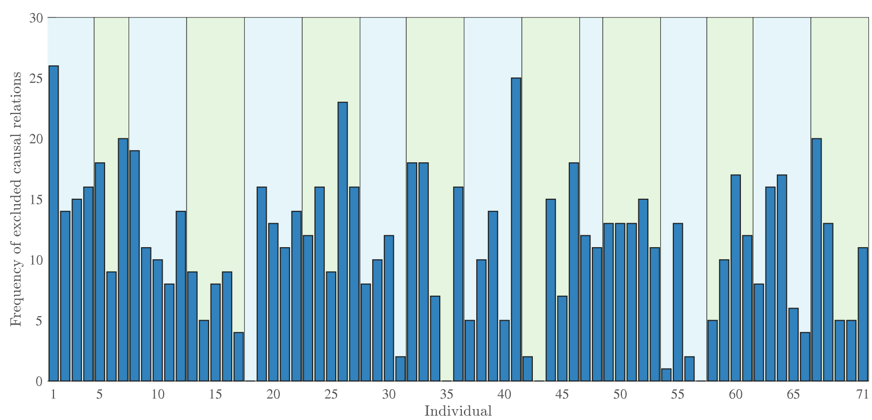

Fig. 7. Frequency of excluded causal relationships for each individual.

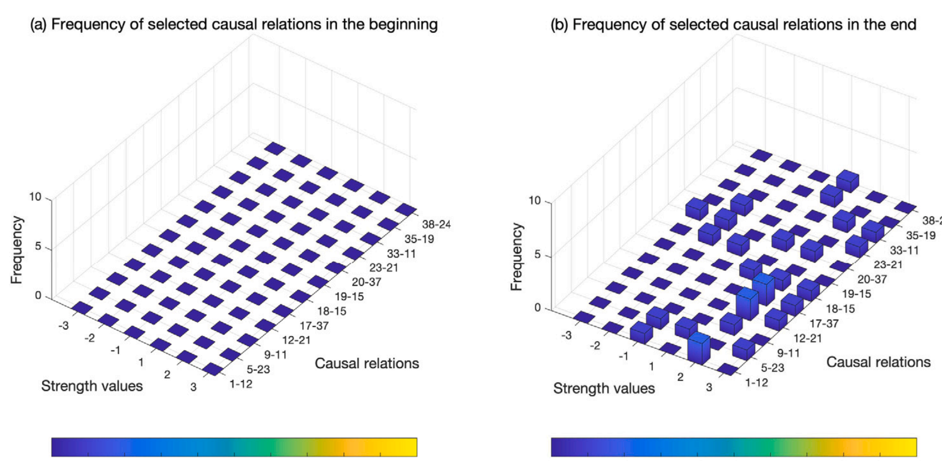

Fig. 8. Some examples of causal relationships that do not exist in the beginning maps as in (a) but exist in the end maps (b).

causal relationships may be based on unintended unlearning. For example, the positive impact of "Supplier selection" on "Environmental sustainability" (39 ⇒ 38) is a logical relationship but has disappeared from students' cognitive maps. The reason for this disappearance might be the CSCL setting with a business simulation, which may direct students' attention to short-term financial performance at the expense of sustainable development. Therefore, the proposed method for assessing learning can help teachers address these unlearning effects by raising these unintentionally disappearing causal relationships as discussion topics in the course. All of the disappeared causal relationships shown in Fig. 6 are summarized with the corresponding strategic issues in Table 5.

The analysis above does not focus on the frequency of each causal relationship found; instead, it examines the causality changes between start maps and end maps overall. The frequency information reflects the importance of each causal relation. However, this way, we consider that inspecting the causality changes overall is sufficient enough to stress the learning effects during the course.

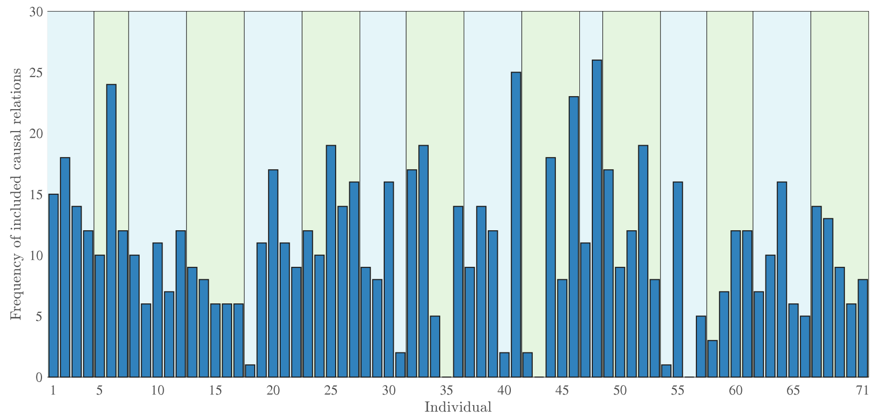

Fig. 9. Frequency of included causal relationships for each individual.

Table 5
Example cases of causal relationships observed regarding Q3.1.

Disappeared causal relationships presented in Fig. 6
(1) Market share (1) ⇒ Market selection decisions (33)
(2) In house R&D (8) ⇒ Investment in production and plants (6)
(3) Buying technology and design licenses (9) ⇒ TCSR (41)
(4) Feature offered (11) ⇒ Brand, company image (34)
(5) Internet loans (18) ⇒ TCSR (41)
(6) Competition in the market (21) ⇒ Promotion (30)
(7) Employee training and education (25) ⇒ R&D employee turnover (27)
(8) Market selection decisions (33) ⇒ Long-term profitability (23)
(9) Brand, company image (34) ⇒ Consumer price elasticity (26)
(10) Environmental sustainability (38) ⇒ Internet loans (12)
(11) Environmental sustainability (38) ⇒ Long-term profitability (23)
(12) Supplier selection (39) ⇒ Environmental sustainability (38)

Table 6
Some examples of causal relationships observed regarding Q3.2.

Developed causal relationships presented in Fig. 8
(1) Market share (1) ⇒ Product selling prices (12)
(2) Inventory management (5) ⇒ Long-term profitability (23)
(3) Buying technology and design licenses (9) ⇒ Feature offered (11)
(4) Product selling prices (12) ⇒ Competition in the market (21)
(5) Number of shares outstanding (17) ⇒ Equity ratio (37)
(6) Internet loans (18) ⇒ Long-term debt (15)
(7) Sales (19) ⇒ Long-term debt (15)
8) Corporate tax rate (20) ⇒ Equity ratio (37)
(9) Long-term profitability (23) ⇒ Competition in the market (21)
10) Market selection decisions (33) ⇒ Feature offered (11)
(11) Capacity allocation (35) ⇒ Sales (19)
(12) Environmental sustainability (38) ⇒ Growth of the company (24)

Fig. 7 displays the total numbers of removed causal relationships concerning the beginning and end of the simulation process, individual by individual. In other words, it demonstrates how many relationships that appeared in the initial maps have disappeared in the end maps for each individual. According to the figure, one can observe that majority of students have excluded a considerable number of cause–effect relationships by the end of the course, which were initially considered important based on the knowledge gained during the course. For instance, student "1" has removed 26 causal relationships, followed up by student "41" removing 25 causal relations. In the orientation stage, the individual cognitive maps could have been relatively simple in terms of structural attributes and could have involved cause–effect relationships that do not offer much to the success of the strategic decision-making process. These cognitive models were probably adjusted reasonably through differentiation as students changed their unique views of the situation based on the learning. Additionally, exposure to interactions with other team members and learning through group processes might also cause students to change their opinions during the task. Consequently, we can see a removal of such a number of causal relationships from their initial maps. Moreover, students "18", "35", "43", and "56" have not removed any cause–effect relations, which they considered initially. Further, it is noteworthy that even though causality disappearance at the individual level is presented in the figure, it does not tell much about the changes at a group level. This clearly shows the need for performing the assessment of the outcomes and effects of teaching/learning both on the group and the individual level.

6.3. Examining the causal relationships that exist at the end maps but not in the beginning maps (Q3.2)

In this examination, we observed those 120 causal relationships that have emerged in the end maps, and the frequency distributions of some of them are presented in Fig. 8. This means that the students have learned the significance of some relationships to be considered in the strategic decision-making process to achieve reliable performance. Fig. 8 depicts several examples of such learned effects. First, the emergence of the positive impact of "Product selling prices" on "Competition in the markets" (12 ⇒ 21), indicates that students have learned how pricing decisions impact competition. Second, the emergence of the negative impact of "Sales" on "Long-term debt" (19 ⇒ 15) indicates that students have learned that they need sales revenue to be able to amortize their long-term debt. Third, the emergence of the positive relationship between "Number of shares outstanding" and "Equity ratio" (17 ⇒ 37) indicates that students have learned that they can issue shares in order to manage their level of leverage and financial risk. Even though the absolute numbers of these emerged relationships are not very high, these can clearly be considered a positive outcome of the learning process, as their existence in the cognitive structures of the students makes sense. One could therefore conclude that the teaching is designed well in this aspect but should probably influence more than just these few students in the same way, as long as the emerging relationships are considered correct and important. Table 6 summarizes all of the causal relationships shown in Fig. 8 with the related strategic issues.

Fig. 9 illustrates the frequency of developed causal relationships for each individual by the end of the simulation process. As the figure depicts, it is clear that most students have changed their cognition by developing a significant number of cause–effect relationships for success in the business simulation work. However, there can also be seen that three students (students "35", "43", and "56") have not added any new effects to their cognitive structures. As they also have not removed any causal relationships (as shown in Fig. 7), it reveals that these three students used the same cognitive maps in the beginning and end.

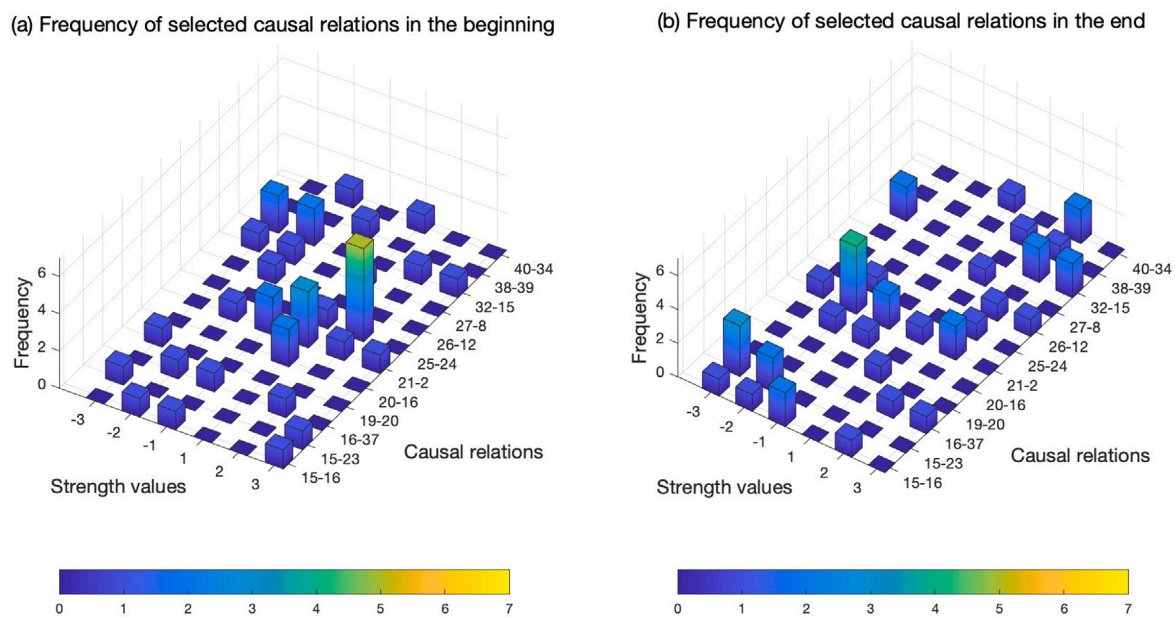

Fig. 10. Directional changes of the causal relationships — their frequency in the beginning (a) and at the end (b).

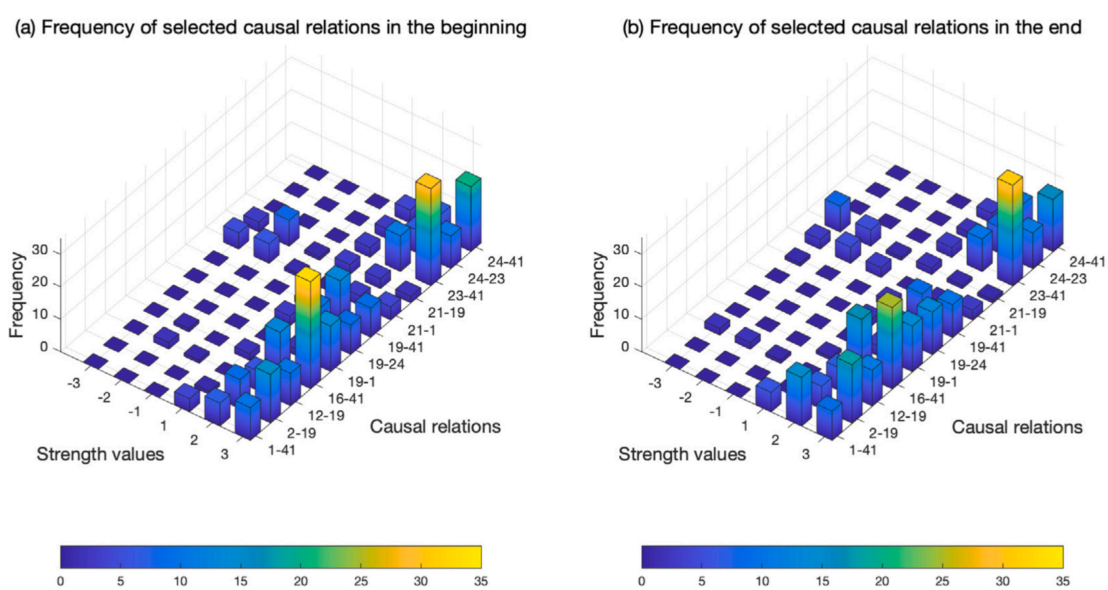

Fig. 11. Most robust causal relationships in the beginning (a) and at the end (b).

6.4. Examining the directional changes of causal relationships (Q3.3)

We also expected that the course learning might result in changes in the direction of the causal effects yielded by students. Accordingly, this assessment was led to investigate the directional changes in the causal relationships from the beginning maps to the end maps. We examined the cases where the direction has gone up, down, or completely changed (e.g., positive → negative or vice versa). Fig. 10 shows the frequency distributions of the causal relationships with the largest directional/magnitude changes obtained in this analysis.

Let us consider some cases presented in Fig. 10 more closely as examples. When we see the relation from "Corporate Tax rate" to "Dividends" ($20 \Rightarrow 16$), it was recognized as a positive effect initially, but it was characterized as a negative effect in the end. Moreover, the relation of "Interest rates" to "Long-term debt" ($32 \Rightarrow 15$) has a frequency vector $(2, 2, 0, 0, 1, 1)$ for $(-3, -2, -1, 1, 2, 3)$ in the beginning, but which is $(2, 0, 0, 0, 2, 2)$ in the end. That is, this relationship was likely negative (negative 4, positive 2) initially, but it has changed to positive (negative 2, positive 4) in the end. In this way, we identified the directional changes of the causal relationships from beginning to end. To get more clear view, these relationships are also summarized with corresponding strategic issues in Table 7. Additionally, weighted sums $[(-3)\times n_1 + (-2)\times n_2 + \cdots + 3\times n_6$, where $n_1, n_2, \ldots, n_6$ are the corresponding frequencies] of each relationship in the beginning and end are presented. This clarifies how each of these relations has updated from positive to negative or other way around. However, notice that some of these changes are not that strong, but all results provide support or, at minimum, evidence to the fact that students' opinions on the strategic interpretations have changed during the process.

Results from the fsQCA analysis. As we discussed in Section 5.3, we also tried to examine the changes of causal relationships (in cognitive maps) from the beginning to end using a fsQCA analysis. In short, to evaluate the hypotheses (see Table 4) derived, all strength values of

Table 7
The best possible cases of the findings related to Q3.3.

Causal relationships presented in Fig. 10	Weighted sum (beginning)	Weighted sum (end)
Long-term debt (15) ⇒ Dividends (16)	0	−5
Long-term debt (15) ⇒ Long-term profitability (23)	0	−13
Dividends (16) ⇒ Equity ratio (37)	−1	5
Sales (19) ⇒ Corporate tax rate (20)	−3	1
Corporate tax rate (20) ⇒ Sales (16)	2	−3
Competition in the market (21) ⇒ Demand (2)	4	−8
Employee training and education (25) ⇒ Growth of the company (24)	11	0
Consumer price elasticity (26) ⇒ Product selling prices (12)	−2	5
R&D employee turnover (27) ⇒ In-house R&D (8)	−4	1
Interest rates (32) ⇒ Long-term debt (15)	−5	4
Environmental sustainability (38) ⇒ Supplier selection (39)	−1	3
Supply chain ethics (40) ⇒ Brand, company image (34)	−1	3

Table 8
The results of the average consistency and coverage measures for all hypotheses.

$A \Rightarrow B$	Consistency	Coverage
(H_{01}) negative, negative	0.2132	0.2132
(H_{04}) **negative, zero**	**0.7148**	**0.1272**
(H_{07}) negative, positive	0.0720	0.0116
(H_{02}) zero, negative	0.1663	0.7215
(H_{05}) zero, zero	–	–
(H_{08}) **zero, positive**	**0.8337**	**0.5784**
(H_{03}) positive, negative	0.0113	0.0653
(H_{06}) **positive, zero**	**0.5900**	**0.8728**
(H_{09}) positive, positive	0.3987	0.4100

the causal relationships in the starting and end maps were collected for each individual. Once the strength vectors of each individual for start and end maps were obtained, trapezoidal fuzzy memberships were computed by using expertly defined trapezoidal membership functions. For each negative, zero and positive case, trapezoidal membership functions were defined by the experts as $\mu_{negative} \sim \Pi(x;-3,-3,-1,0)$, $\mu_{zero} \sim \Pi(x;-1,0,0,1)$, and $\mu_{positive} \sim \Pi(x;0,1,3,3)$. Using these membership values, next, consistency and coverage scores were computed for each individual. As the last step, computed consistency and coverage values of each individual were averaged, and the resulting mean scores are presented in Table 8.

In Table 8, it is apparent that the case of "zero, positive" has high support from the evidence in terms of consistency of 0.8337 (that surpasses the threshold of "high") and coverage of 0.5784. This result suggests that H_{08} was the most consistent claim with the data, implying that causal effects that were not part of the beginning maps seemed to be realized as necessary and positive at the end maps. Moreover, the "negative, zero" case appears to be supported by a good consistency value (0.7148) though its coverage value was not considerably high. Additionally, we can also observe that an acceptable consistency of 0.59 and high coverage of 0.8728 provide significant support to the case of "positive, zero". These two findings provide evidence supporting the fact that some causal effects, initially characterized by positive and negative strengths, were omitted (zero) by the end of the simulation task. Overall, the evidence from this analysis (zero → positive, negative → zero, and positive → zero) highlights that individuals have made most of the non-existent cause–effect relations existent and positive, and some existent positive and negative effects insignificant by the end of their decision-making process as a result of learning. We did not find significant evidence supporting the other hypotheses concerning the rest of the consistency and coverage scores. However, it is noteworthy that the case "Zero, Zero" was not investigated directly, as due to the representation of every causal map using a 41 × 41 matrix but allowing only the use of 13 strategic issues increases the number of non-existing relationships artificially. Also, the practical relevance of this relationship is limited. The results in Table 8 are based on the strategic issues that existed, at least in the beginning or end maps. Overall, Table 8 suggests that the direct effect of teaching/learning in the specified CSCL course was a change in the polarity of the causal relationships, as the rules suggesting change are the most consistent ones with the available data. More specifically, the learning was reflected in removing a negative causal relationship (second highest consistency) and in removing positive causal relationships (third highest consistency). The most notable effect can be summarized as the emergence of positive causal relationships (the highest consistency) as a result of learning. Not contrary to expectations, some causal relationships remained in the cognitive structures and retained their polarity ("positive, positive" being more consistent with the data than "negative, negative"). It is also visible that there were some isolated cases of the reversion of the polarity of the causal relationships ("negative, positive" and "positive, negative" not having zero consistency with the available data). The analysis does confirm the expected results, but it also suggests that the negative causal relationships are less emergent and more removed than the positive ones.

The analysis of the polarity changes of causal relationships has, so far, been focused on the overall course level. It is also possible to apply the fsQCA tools to investigate the polarity changes in specific causal relationships. Table 9 provides several examples of the results that can be obtained this way. One can see that the results are different for different causal relationships. For example, the causal relationship Employee training and education (25) ⇒ Growth of the company (24) is shown to be such that it tended to disappear from the cognitive structures of those that initially considered it to be positive, while for some it remains positive in their cognitive structures. If it emerged, then with a negative polarity. We, however, need to admit that the formulation of the actual causal map creation task that restricted the use of strategic issues to 12 (+ the compulsory total cumulative shareholder returns) artificially increases the number of zeros in the adjacency matrices of the causal maps. Therefore in this specific real-life applicability study, the consistencies of the rules starting with the nonexistence of the causal relationship in the beginning maps, might be undervalued.

6.5. Examining the most robust causal relationships (Q3.4)

This assessment examines the causal relationships that are consistent based on students' opinions from start to end. In particular, the causal relationships that existed in both start and end maps, which had an increased or decreased frequency by the end, or being with the same frequency, were investigated. This analysis resulted in 174 relevant causal relations, the most robust cases of which are summarized with corresponding frequencies in Fig. 11. Notice that overall frequencies of the presented causal relationships in the figure are higher than 10.

Table 9
The results of the investigation of polarity changes of specific causal relationships (selected examples).

15⇒16	Consistency	Coverage	16⇒37	Consistency	Coverage
(H_{01}) negative, negative	0.5000	0.2500	(H_{01}) negative, negative	0.0000	0.0000
(H_{04}) negative, zero	0.5000	0.0152	(H_{04}) negative, zero	1.0000	0.0290
(H_{07}) negative, positive	0.0000	0.0000	(H_{07}) negative, positive	0.0000	0.0000
(H_{02}) zero, negative	0.0441	0.7500	(H_{02}) zero, negative	0.0000	0.0000
(H_{08}) zero, positive	0.0147	1.0000	(H_{08}) zero, positive	0.0147	0.5000
(H_{03}) positive, negative	0.0000	0.0000	(H_{03}) positive, negative	0.0000	0.0000
(H_{06}) positive, zero	1.0000	0.0152	(H_{06}) positive, zero	0.0000	0.0000
(H_{09}) positive, positive	0.0000	0.0000	(H_{09}) positive, positive	1.0000	0.5000
21⇒2	Consistency	Coverage	25⇒24	Consistency	Coverage
(H_{01}) negative, negative	0.3000	0.1429	(H_{01}) negative, negative	0.0000	0.0000
(H_{04}) negative, zero	0.3333	0.0164	(H_{04}) negative, zero	0.0000	0.0000
(H_{07}) negative, positive	0.3000	0.3000	(H_{07}) negative, positive	0.0000	0.0000
(H_{02}) zero, negative	0.0635	0.5714	(H_{02}) zero, negative	0.0154	1.0000
(H_{08}) zero, positive	0.0159	0.3333	(H_{08}) zero, positive	0.0000	0.0000
(H_{03}) positive, negative	0.4000	0.3000	(H_{03}) positive, negative	0.0000	0.0000
(H_{06}) positive, zero	0.4000	0.0328	(H_{06}) positive, zero	0.8333	0.0725
(H_{09}) positive, positive	0.2000	0.3000	(H_{09}) positive, positive	0.1667	1.0000
20⇒16	Consistency	Coverage	40⇒34	Consistency	Coverage
(H_{01}) negative, negative	0.0000	0.0000	(H_{01}) negative, negative	0.0000	0.0000
(H_{04}) negative, zero	0.0000	0.0000	(H_{04}) negative, zero	1.0000	0.0147
(H_{07}) negative, positive	0.0000	0.0000	(H_{07}) negative, positive	0.0000	0.0000
(H_{02}) zero, negative	0.0290	1.0000	(H_{02}) zero, negative	0.0145	1.0000
(H_{08}) zero, positive	0.0000	0.0000	(H_{08}) zero, positive	0.0145	0.5000
(H_{03}) positive, negative	0.0000	0.0000	(H_{03}) positive, negative	0.0000	0.0000
(H_{06}) positive, zero	1.0000	0.0290	(H_{06}) positive, zero	0.0000	0.0000
(H_{09}) positive, positive	0.0000	0.0000	(H_{09}) positive, positive	1.0000	0.5000

Table 10
The best possible cases of the findings related to Q3.4.

Causal relationships presented in Fig. 11	Weighted sum (beginning)	Weighted sum (end)
Market share (1) ⇒ TCSR (41)	48	63
Demand (2) ⇒ Sales (19)	64	68
Product selling prices (12) ⇒ Sales (19)	37	36
Dividends (16) ⇒ TCSR (41)	125	110
Sales (19) ⇒ Market share (1)	46	48
Sales (19) ⇒ Growth of the company (24)	51	51
Sales (19) ⇒ TCSR (41)	55	47
Competition in the market (21) ⇒ Market share (1)	−10	−11
Competition in the market (21) ⇒ Sales (19)	−11	−28
Long-term profitability (23) ⇒ TCSR (41)	115	116
Growth of the company (24) ⇒ Long-term profitability (23)	47	51
Growth of the company (24) ⇒ TCSR (41)	78	71

By looking at Fig. 11, one can see that some cause–effect relationships between strategic issues have been frequently employed and reported by the students throughout the simulation activity. To get more insights into the presented results, let us consider and interpret some cases from Fig. 11. According to the students' points of view, "Dividends" (16) and "Long-term profitability" (23) have been the essential features to TCSR (41) in the whole process. This is obvious as the students followed the economic principles and considered that maximizing TCSR includes the dividends paid by the company to shareholders, the interest generated by the profits for the shareholders, etc. Besides, the students perceived that the relations from "Competition in the market" (21) to the "Market share" (1) and "Sales" (19) as the most substantial negative effects. In general, competition in the market occurs because there are a large number of different buyers and sellers. It allows the price to change according to the response to supply and demand. This might be the reason why students put their opinions that increasing competition in the market influences in reducing sales and demands. Moreover, all of these relationships, together with weighted sums at the beginning and end, are summarized in Table 10.

To get more evidence, we specifically analyzed the most robust cases according to the individuals for each group and found results are summarized in Table 11. From the table results, it is confirmed that the relations from "Dividends" (16) and "Long-term profitability" (23) to the TCSR (41) are the most visible cases among the groups of students. Note that if Fig. 11 or Table 10 contain causal relationships that are not desirable (or illogical), then it indicates that the CSCL event did not succeed in removing these potentially incorrect preconceptions.

In summary, the findings of these analyses highlight the most significant strategic issues and their cause–effect relationships and make it possible to identify different patterns of causality changes in the cognitive maps from start to end. Having these provided clear evidence to support the fact that the course learning has had a considerable effect on the students' perception changes. It is noteworthy that we discovered a total of 455 cause–effect relationships in the causal network on the strategic landscape from the data. It indicates that the students have contributed to many functions of company attributes to gain overall success in their decision-making process. There was no explicit limitation for designing cause–effect relationships in the cognitive maps (except for the upper limit of the number of used strategic issues), the

Table 11
Most consistent causal relationships (CRs) at the group level in the beginning and the end (each case is presented by checking how many members in the group used it).

Group	CRs	Beginning			End		
		3	4	All members	3	4	All Members
Group 1	19 → 23	✓			✓		
	23 → 41		✓				✓
Group 3	1 → 41	✓			✓		
	15 → 41	✓			✓		
	16 → 41		✓		✓		
	23 → 41		✓		✓		
Group 4	16 → 41			✓			✓
	23 → 41		✓			✓	
Group 5	16 → 41		✓			✓	
	19 → 41	✓			✓		
	23 → 41		✓			✓	
Group 7	19 → 24	✓			✓		
	23 → 41	✓			✓		
Group 8	2 → 19	✓			✓		
	16 → 41	✓				✓	
Group 10	2 → 19		✓		✓		
	19 → 23	✓			✓		
	23 → 41	✓				✓	
Group 12	16 → 41			✓	✓		
Group 15	16 → 41			✓			✓
	23 → 16	✓			✓		
	23 → 41		✓			✓	
Group 16	19 → 1	✓			✓		
		2	3	all members	2	3	all members
Group 6	19 → 24		✓		✓		
	23 → 41		✓		✓		
Group 9	1 → 41		✓				✓
Group 13	1 → 41	✓				✓	
	12 → 41		✓		✓		
	15 → 41	✓				✓	
	19 → 41		✓			✓	
	24 → 41			✓			✓
	34 → 41	✓				✓	
Group 14	16 → 41	✓				✓	
Group 2[a]	2 → 19	✓			✓		
Group 11[b]	16 → 41			✓			✓

[a]Included only three students.
[b]Included only two students.

only thing was individuals were expected to reflect their knowledge and course learning.

7. Conclusion, limitations, and future work

In conclusion, the present study demonstrated the effectiveness of the proposed cognitive mapping-based approach for assessing learning in the context of CSCL in terms of the students' academic success and teacher's perspectives. We proposed an unsupervised approach to the assessment of learning outcomes that is explorative and allows for the identification of the actual effects of the teaching event on the students — both on individual and group levels. Table 12 summarizes the empirical results obtained through each analysis for each research question and their implications.

The results from all analyses implied that the students have had a positive learning environment, and also teacher's guidance and instructions were successful to some extent. Overall, this study has made several significant contributions to the existing literature, which can be summarized as follows:

– We have proposed a general methodology for the application of cognitive maps in the unsupervised (exploratory) assessment of the outcomes of learning to be used for the management of knowledge enhancement process. The methodology reflects both individual and group effect of learning on the cognitive structures of the learners. A comprehensive methodology of this kind has, so far, not been proposed in the literature.
– We showed the ability of the proposed unsupervised learning assessment methods to identify persistent, emerging, and disappearing causal relationships, to assess the effect of learning on cognitive diversity, etc.
– We offered a better understanding of using a cognitive mapping approach to examine a particular teaching–learning event in a CSCL environment by designing the teacher's and students' roles and targeted activities that lead to meaningful and correct relationships between concepts of interest in a specific subject/area.
– We showed the applicability of distance ratio measures, fsQCA measures, and histogram frequencies in cognitive mapping-based studies in educational research.

However, it should be emphasized that the real-life applicability study presented in this paper has some limitations that might prevent us from showing the full potential of the proposed unsupervised learning assessment methods. One of the limitations was the limit of 12 strategic issues to be used at most in the causal maps, along with the total cumulative shareholder returns. This slightly complicates the interpretability of the results obtained through the fsQCA-based methods. Also, for the individual-level analyses, we have, in several cases, presented only selected causal relationships to show the results and interpretations, mainly those that were significant in terms of the students' perspectives. Due to the limited space in the paper, it was not possible to present

Table 12
Overview of the findings obtained using the proposed methods in the CSCL-based applicability study and their implications.

Analysis	Result	Conclusion
Distance ratio-based analysis (Q1)	Varying diversity within the group level in terms of distance ratios	Cognitive diversity within a group was reduced to some extent in many groups as a result of teaching/learning.
Assessment of perceived causalities (Q2)	A significant change in students' perceptions of learning by the end of the course in terms of the strategic concepts and their cause–effect relations in the decision-making process	Students' understanding of the strategic concepts and cause–effect relationships in the decision-making process improved throughout the course.
Frequency-based analysis + fsQCA analysis (Q3)	(1) Significant changes in the directions of causal relationships in terms of the negative, non-existence, and positive from the starting to end maps (2) Strategic issues and cause–effect relationships that were very important to success in the strategic decision-making process	Course learning has considerably affected the students' perception change and knowledge improvement.

Table A.1
An example of a 41 × 41 adjacency matrix.

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

the obtained results in their entirety. Nevertheless, we are convinced that the selection is sufficient for the illustration of the applicability of the proposed methods. Despite the limitations, as far as we know, this is the first attempt that cognitive maps, along with distance ratios, causal frequencies, and a fsQCA, have been utilized to describe the outcomes of a learning process and the effects of teaching. In particular, we demonstrated that these tools are potent techniques for comprehensively examining the teaching–learning process. Accordingly, a number of possible future research directions using these tools are evident, for example:

– Examine the effectiveness of online class versus in-person class teaching through an empirical study using the proposed method.
– Extend the proposed approach as an alternative to the method presented by Shen et al. (2019) to help the teachers to understand students' learning challenges and improve their efficacy. In principle, any application involving cognitive mapping to assess individual learning, group-level learning, or both in a learning/training activity can be reconsidered with the proposed approach.
– Investigate how teachers' practical knowledge, experience, and teaching strategy influence effective teaching from the teachers' perspective and learning from the students' perspective focusing on a teaching-class activity.

Additionally, this study specifically provides a better understanding of the principles of fsQCA analysis in terms of its applicability for examining students' perceptions and expert knowledge developments, particularly in a CSCL environment. Therefore, this study contributes to educational research, as studies based on the analysis of cause–effect relationships to study the effects of individual + collaborative cognition on learning and performance are uncommon.

CRediT authorship contribution statement

Mahinda Mailagaha Kumbure: Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Anssi Tarkiainen:** Conceptualization, Data curation, Writing – review & editing, Supervision. **Jan Stoklasa:** Conceptualization, Formal analysis, Methodology, Writing – review & editing, Supervision. **Pasi Luukka:** Conceptualization, Writing – review & editing, Supervision. **Ari Jantunen:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Adjacency matrix

See Table A.1.

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