A Knowledge Integration Approach for Organizational Decision Support

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ABSTRACT

This study proposes a new methodology that facilitates organizational decision support through knowledge integration across organizational units. For this purpose, this study develops a decision support loop and explains how to organize individual knowledge related to a specific business problem and formulate and test the organized knowledge using cognitive modeling techniques for decision support. This study discusses the proposed approach in the context of an application case involving a beverage company. The application case shows the validity and usefulness of the proposed approach.

Keywords: cognitive modelling; knowledge integration; organizational decision support

INTRODUCTION

Knowledge management (KM) can be defined as the uncovering and managing of various levels of knowledge within individuals and teams and within an organization. The aim of KM is to improve organizational performance. One of the prerequisites for successful KM is an appreciation of what Nonaka (1994) described as "tacit" knowledge. Effective KM requires such "tacit" knowledge to be transformed into "explicit" knowledge and then organized accordingly (Brown & Dugid, 1998). Integrating individual knowledge from diverse areas into organizational knowledge leads not only to new knowledge but also to new understanding (Cai, 2006; Huber, 1991; Siau 2000). This in turn helps decision makers choose the appropriate action to achieve organizational goals (Brown & Dugid, 1998; King, 2006; Stein, 1995).

However, competitive advantage results from applying knowledge, rather than knowledge itself (Alavi & Leidner, 2001). However, most KM research (Davenport, De Long, & Beers, 1998; Grover & Davenport, 2001; Kankanhalli, Tan, & Wei, 2005; Lee & Kim, 2001; Sambamurthy

& Subramanu, 2005; Xu, Tan, & Yang, in press) has focused on identifying, storing and sharing knowledge for efficient and effective transaction processing. There has been little research into the application of organizational knowledge or KM in the core business management tasks of decision making and strategy development. Yet the scope of knowledge application in these top-level tasks is organization wide. Knowledge application at this level, therefore, would influence organizational performance even more than knowledge management in transactions processing, where the scope is more localized. The research gap shows the need to shift the focus away from obtaining and storing knowledge to using it appropriately for business decision making.

Based on the research needs outlined above, this study aims to propose a new methodology for organizational decision support through knowledge integration across organizational units. Bridging the gap between having knowledge and using it is a very valuable endeavour, both for theorists from the descriptive perspective and for practitioners from the normative perspective. For this purpose, this study develops a decision support loop. The developed decision support loop explains (1) how to organize individual knowledge related to a specific business problem using cognitive modeling, and (2) formulate and test the problem reflected in the organized knowledge using cognitive matrix and causal path identification for decision support. We apply the proposed approach to a decision support case of a beverage company. The application case shows the validity and usefulness of the proposed approach.

This paper is organized as follows. First, we propose a decision support loop formed by integrating individual knowledge as it resides in mental models into an organizational model. Next, we compare the approach of this study with other approaches. We then discuss the proposed model based on its application to a real-world managerial problem.

DECISION SUPPORT THROUGH KNOWLEDGE INTEGRATION

This study proposes a decision sup-

Figure 1. Decision support loop

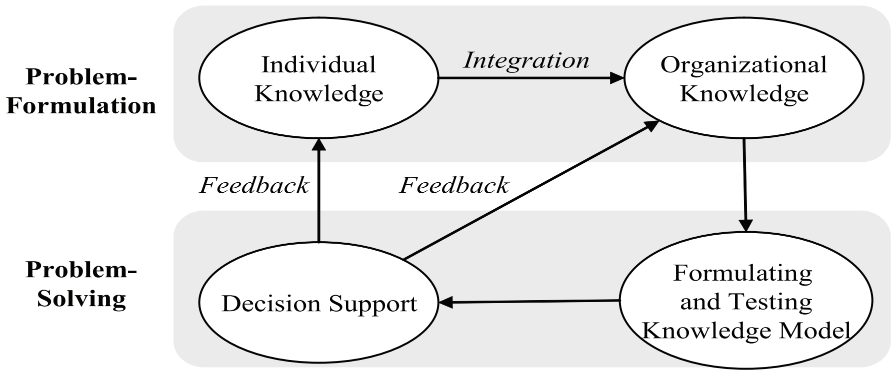


Table 1. An overview of a cognitive modeling methodology for the decision support loop

Step	Objective	Task	Details
Individual knowledge	Lower-level cognitive model generation	Specify goals Identify causal factors Identify causal connections	Use brainstorming, interview, document analysis, and survey
Organizational knowledge	Higher-level cognitive model generation	Integrate lower-level cognitive models	Link maps based on common causal factors Resolve discrepancies through meetings
		Assign causal values	Use an eigenvector assignment algorithm
Formulating/testing knowledge model	Identification of significant causal paths	Identify causal impact paths and compute the causal values	Use a causal path computation algorithm
Decision support	Identification of core factors	Identify the most positive/negative impact factor for the organizational goal	Compute the most positive/negative impact value for the goal factor
	Identification of core business activities	Identify the path that makes the most positive impact factor stronger	Compute the largest path value for the most positive impact factor
		Identify the path that makes the most negative impact factor weaker	Compute the smallest path value for the most negative impact factor

port loop through knowledge integration across multiple knowledge sources, as illustrated in Figure 1. Based on an identified managerial problem, individual knowledge is gathered and then integrated into organizational knowledge, which captures and defines the problem. This constitutes the problem formulation phase. Managerial problems commonly entail two stages in their resolution: problem formulation and problem solving (Smith, 1989). To provide a linkage between knowledge integration and decision support, the organizational knowledge model is formulated and tested, and then decision guidelines are generated based on the knowledge model. This constitutes the problem-solving phase.

To facilitate this decision support loop, we propose a cognitive modeling methodology. Table 1 illustrates an overview of the proposed methodology. We will discuss the goal, tasks, and details of each step in the following sections.

Individual Knowledge

Knowledge is useful only when it is related to a target task or problem. If the knowledge is not helpful in a given situation, it can be deemed not knowledge at all in that situation, even though it might be in another situation. Individual knowledge means individual and partial mental model knowledge related to the target problem. As a way for capturing knowledge, cognitive modeling has been used to represent relationships that are perceived to exist among the attributes and/or concepts of a given environment or problem (Eden, 1988; Fiol & Huff, 1992). The cognitive modeling method thus can be applied to capture individual (departmental) or partial knowledge (Lenz & Engledow, 1986).

As one of the tools for cognitive modeling, the cognitive map has been widely used in previous research (e.g., Axelrod, 1976; Siau & Tan, 2005, 2006; Zhang, Wang, & King, 1994). Cognitive mapping techniques are known as effective tools to elicit and represent human cognition (Siau & Tan, 2005). In this study, the cognitive map is represented in matrix as well as diagram. Diagram representation is used for capturing cause-effect relationships in an organization because it is relatively easy to see how each of the causal factors relates to each other. Matrix representation is used for identifying the most effective causal path because it is convenient to apply a mathematical algorithm.

A prior cognitive model or belief structure shapes each department's interpretation of information, and affects its decision making or task processing (Huber, 1991). These cognitive models vary across organizational units, depending on their different responsibilities and viewpoints. For example, the marketing team might have knowledge regarding the way in which delays in delivery affect sales volume, but not know how such a delivery delay could be minimized. In contrast, the delivery team might know little about increasing sales but a lot about minimizing delivery delay. In this way, each team has a partial mental model or individual team knowledge about the target issue.

In this study, the cognitive model is generated through three tasks. The first task, specifying the goal, facilitates the generation of a robust cognitive map from the rest of the tasks because goals serve as guides to action (Simon, 1964). Clarifying the goal of each functional unit, therefore, helps to capture the cause-effect relationships among cognitive elements. A number of techniques can be used to generate and validate the cognitive maps of the organization: brainstorming, interview, document analysis, and survey.

Organizational Knowledge

In real-world situations, not only human employees but also each functional department tends towards a silo viewpoint and understanding. Before knowledge is integrated across functional areas, each department may diagnose a business problem from its own viewpoint. Thus, each department may identify a core issue and suggest a solution without first adopting a cross-functional viewpoint. For this reason, cross-domain knowledge integration and sharing have been suggested as an important issue for KM (e.g., Hanse, 2002; Nadkarni & Nah, 2003; Nilakanta, Miller, & Zhu, 2006) and for enhancing organizational performance (e.g., Cai, 2006; Nambisan & Wilemon, 2000).

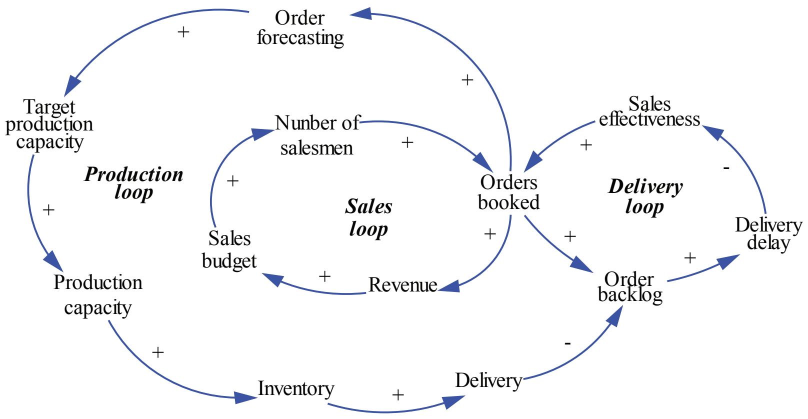
For organizational knowledge modeling, we generate an integrated global (higher-level) cognitive model by combining local (lower-level) cognitive models, which leads to a combined view for the problems. The integrated cognitive model represents the cognitive model of the group, which consists of individual departments. Local reasoning is done at each functional (operating or product) unit to form its own local cognitive model. However, global reasoning is necessary to combine local cognitive models into an integrated cognitive model. Because cognitive maps tend to impose structure on a vague situation, group members can gain a clearer understanding of problems and opportunities (Weick & Bougon, 1986).

In order to combine the local cognitive maps, we first identify the common causal factors between any two local cognitive maps, and link the maps based on these factors. Each common causal factor plays the role of a coupling device. In turn, the next local cognitive map is joined with the previous result. In this way, the combination process continues until all local cognitive maps are exhausted. While the local cognitive maps are being combined into a global cognitive map, various discrepancies between the maps might arise. In that case, these discrepancies should be detected and resolved through the meeting in which the related functional units participate in order to create a complete global cognitive map.

Integrating the different bodies of individual knowledge constitutes organizational knowledge in that a network of knowledge is produced across different areas in the organization. Organizational knowledge is a specific knowledge model related to a target concern or problem. It can also be modeled on a cognitive model. For example, for the purpose of revenue enhancement, individual knowledge from the sales, production, and delivery teams can be integrated as in Figure 2. This integrated organizational knowledge can explain many issues to the various teams. The teams can then collaborate and know how sales are affected by delivery delay and how they can shorten delivery delay. That is, the organizational knowledge model regarding the target issue shows all the relationships among elements across all areas, and it helps decision makers understand the problem clearly and choose appropriate actions to achieve organizational goals. As such, organizational knowledge constitutes the core competency of management.

Although teams and individuals create their respective knowledge models, work that is shared among teams calls into use

Figure 2. Representation of organizational knowledge using cognitive maps



Formulating and Testing Knowledge Model

separate bodies of individual knowledge and generates an organizational knowledge model as well. The organizational knowledge model becomes a basis for understanding the dynamic complexity of the target situation. It enables decision makers and subunits to understand the entire structure of the target business problem (example.g., how to increase revenue). It also helps them assess the behavioural mechanism involved, thus facilitating the choice of appropriate actions to achieve organizational goals.

For the purpose of decision support, the most important thing is to identify several decision options and validate the best option for solving the problem at hand. For this purpose, the organizational knowledge model must be translated into an analyzable form. Although cognitive maps improve communication and comprehension among their users, they may not render an organizational knowledge model adequately analyzable.

There are various ways to analyse a cognitive model. One alternative is to investigate causal paths. This aims to identify the paths leading to either causes or effects for each causal factor. For this purpose, the organizational cognitive model should be analysed in terms of the strength of the impact between causal factors. The cognitive model includes the indirect causal paths as well as the direct causal paths. Direct causal paths easily can be identified from the cognitive map, but it is difficult to do so with indirect causal paths. In addition, there are usually multiple indirect causal paths. In this context, the aim is to identify the causal paths that have the maximum causal impact among all causal paths, regardless of whether the impact is direct or indirect. To capture those causal paths, some studies have proposed methods that combine heuristic algorithms with the cognitive model (Kwahk & Kim, 1999; Zhang et al., 1994).

Table 2 illustrates how to create and

Table 2. Creating and formulating a knowledge model

Objective	Task	Output	Tools
Cognitive model generation	Specify goals	Goal statement	Brainstorming Interview Document analysis Survey Eigenvector algorithm
	Identify causal factors - List all causal factors - Cluster the causal factors	Causal factor list	
	Identify causal connections - Identify the relationships between clusters - Identify the relationships between causal concepts	Cluster relationship diagram Causal factor relationship diagram	
	Assign causal values - Conduct pair-wise comparison - Compute eigenvectors	Pairwise comparison matrix Causal values	
Causal path identification	Initialize cognitive matrix	Cognitive matrix	Matrix operation Causal path computation algorithm
	Compute causal impact paths and values	Causal impact paths and values matrix	

analyse a knowledge model. This method is helpful in analysing the organizational knowledge model because it takes into consideration both the qualitative and quantitative aspects of the cognitive model.

A cognitive map is composed of three components: causal factor, causal value, and causal connection. The main difficulty lies in determining the causal value component. Specification of the causal value is the most challenging problem in generating a cognitive map because it has a qualitative property reflecting people's cognitive status, which cannot be directly measured. Besides, human perception is often inconsistent. Direct scale values have been used by most of the methods for cognitive modeling (Eden & Ackermann, 1989; Zhang et al., 1994). However, this direct assignment approach has limitations in that the procedure is not systematic and the result heavily depends on the analysts' or participants' subjective judgment.

For this method, an eigenvector approach through pairwise comparison was chosen for more systematic determination of causal values. This approach is based on the analytic hierarchy process (AHP) method developed in the 1970s (Saaty, 1980). Strength of the AHP method lies in its ability to structure a complex problem hierarchically and to evaluate the relationships between entities systematically. In the application of AHP method, the eigenvector assignment approach is conducted through pairwise comparison and eigenvector computation.

Pairwise comparison technique starts from the idea that the measurements based on experience and understanding are obtainable only from relative comparisons and not in an absolute way (Saaty, 1980). The intensity of our feelings serves as a scale adjustment device to put the measurement of some objects on a scale commensurate with that of other objects. The results of pairwise comparisons are represented in a form of matrix, called pairwise comparison matrix. A pairwise comparison matrix has cell entries as a scale indicating the relative strength with which elements in one cluster influences other elements in other clusters. This scaling process can then be translated into impact weights. The eigenvalue method is the most preferred approach for the estimation (Saaty, 1980). When a pairwise comparison matrix has a maximum eigenvalue and the corresponding eigenvector whose components are all positive, this eigenvector becomes a ratio scale that are the estimates of relative impact values of elements under comparison. Eliciting causal values in a cognitive map can be viewed as a process that transforms qualitative mental status into quantitative numerical scale. The eigenvector approach provides a way for calibrating a numerical scale, particularly in areas where measurements and quantitative comparisons do not exist.

The completed global cognitive map is analyzed in terms of the strength of the impact between causal factors. Our concern is to identify the causal paths with the maximum causal impact among all causal paths regardless of the direct or indirect impact. These causal paths take negative or positive path values, depending on their causal values. In order to identify the causal path(s) with the maximum causal impact, we adopted the algorithm proposed by Zhang et al. (1994) and extended it to find the paths and values simultaneously. The algorithm produces an n x n matrix called the causal impact path and a value matrix consisting of X_{ij}, where X_{ij} is the set of $\{+p_{ij}, -p_{ij}, +v_{ij}, -v_{ij}\}$: $+p_{ij}$; is a positive causal impact path from element i to j, $-p_{ij}$; is a negative causal path, $+v_{ij}$; is a maximum positive causal impact value corresponding to $+p_{ij}$, and $-v_{ij}$; and is a maximum negative causal impact value corresponding to $-p_{ij.}$ The algorithm is applied iteratively, while either maximum positive value ($+v_{ij}$) or maximum negative value ($-v_{ij}$) can be improved; in other words, until new dominant values cannot be identified (refer to Appendix 1 for the simplified algorithm).

Decision Support

The analyzed knowledge model should suggest guidelines for decisions on managerial problems. A decision guideline can be generated in view of the organizational goal, based on the organizational knowledge model (or cognitive model) and the causal path analysis. An organizational goal is a desired future state of affairs that the organization attempts to realize (Etzioni, 1964). A goal pertains to the future, but it influences current activities. Because organizations are goal-attainment entities, goals play a role in setting directions for its members' activities, leading their thoughts and actions to a specific result (Hamner, Ross, & Staw, 1983). Decision guidelines thus can be identified by analyzing people's thoughts and actions with respect to their organizational goals.

To facilitate decision support, we propose analyzing the organizational knowledge represented in cognitive maps in terms of the causal paths and strengths among the causal factors. The causal impact paths and values among the causal factors can be computed based on the proposed methodology, as mentioned in the previous section. The derived matrix includes the negative path and value as well as the positive path and value for each relationship among the causal factors.

Regardless of the polarity of the impact, it is first necessary to focus on the most effective causal factor in achieving the goal. This factor can be an opportunity, if it has a positive impact, but it can be a problem, if it has a negative impact. It is then necessary to identify the relevant feedback loop paths that strengthen the positive impact and weaken the negative one. For a causal factor with a positive impact, this involves making its positive loop more positive and making its negative loop less negative. For a causal factor with a negative impact, this involves making its positive loop less positive and making its negative loop more negative.

The output from such a process enables a decision to be made on a managerial problem. There are many reasons that update individual and organizational knowledge and upon which the selection of an appropriate option can be made. That is, there is a feedback process from integrated knowledge and decision support to individual knowledge and mental models. This is a kind of organizational learning process. Although decision makers cannot apply the same option and the same knowledge to similar problems in the future, they can now understand the dynamic complexity of the target problem, the structure among the elements, and the behavioural patterns. Decision making via understanding dynamic complexity, based on a cognitive model, enables the acquisition of real leverage in managerial problems (Fiol & Huff, 1992; Senge, 1990; Sterman, 2001).

COMPARISON WITH OTHER APPROACHES

The proposed approach can be compared with other KM methods. Our research focuses on enterprise wide improvement by enhancing managerial decision support by means of organizational knowledge, whereas other KM methods (Davenport, 1998; Davenport et al., 1998; Kankanhalli et al., 2005) aim to obtain better efficiency and effectiveness in task processing by knowledge attainment and knowledge repository management. Due to this difference in approach, other KM methods are more concerned with individual or departmental tasks at the operational level. They highlight declarative knowledge (which is related to each employee's cognitive model) and procedural knowledge (which is stored as document- or database-type knowledge). In contrast, the proposed method that we have presented emphasizes integrating the partial knowledge of different departments and employees into organizational knowledge. By doing so, our method facilitates effective business decision making and strategic planning.

The proposed approach can be compared with other cognitive modeling methods. Several cognitive modeling methods and tools using the cognitive map have been developed in various domains, including business policy establishment, organizational learning, and strategic option development (Eden & Ackermann, 1989; Hall, 1984; Lee, Courtney, & O'Keefe, 1992). However, most cognitive modeling methods emphasize map representation as a knowledge representation scheme rather than as a problem-solving tool (Kwahk & Kim, 1999). The proposed approach provides a representation scheme as well as some guidelines for problem solving, by further investigating the knowledge represented in the cognitive map, based on the analysis of the most effective paths.

The proposed matrix approach also can be compared with system dynamics (Sterman, 2001). System dynamics is a methodology aimed at designing better behaved system, by understanding the target system, especially with feedback loops among system components and behaviour patterns over time. System dynamics attempts to conceptualize any business problem with a causal loop diagram, and formulate and test it after transforming the causal loop diagram into a stock-flow diagram. The standard application of system dynamics includes identifying the core loop and core factors as part of policy development. However, identifying the core loop and core factors relies on either the intuition of the modeler or user, or the somewhat cumbersome simulation testing of several alternatives. While the identification of the core loop and core factors is very critical to the application of system dynamics and effective policy development, little research has been done in the area. By proposing a new method for identifying the core loop and core factors, this study has contributed to system dynamics literature.

APPLICATION CASE

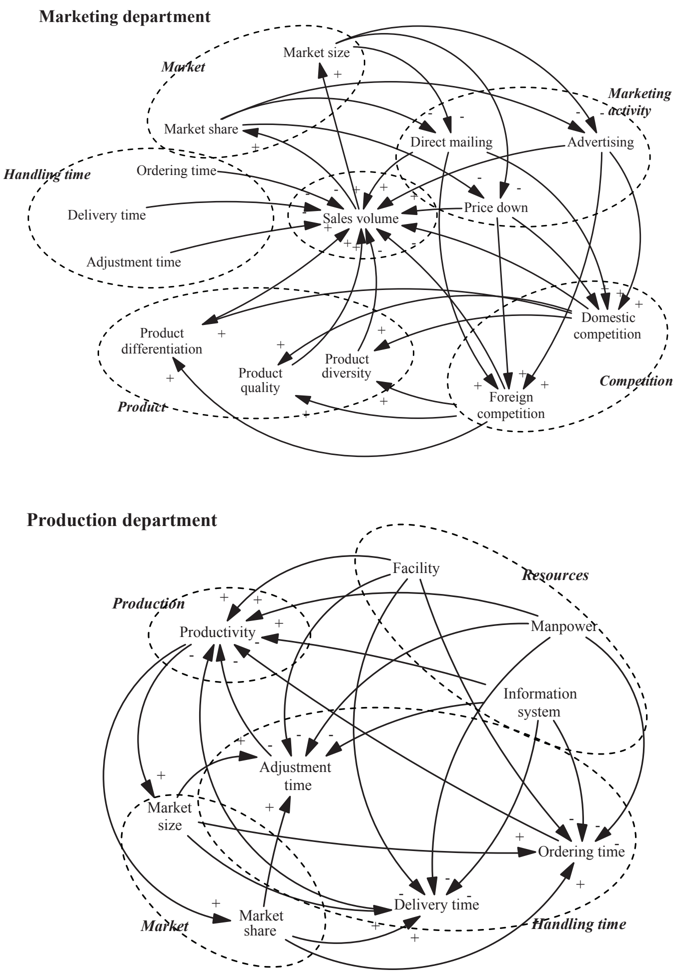
We applied the proposed decision support loop to a beverage company with an annual sales volume of about $600 million. The company was about to start a business process redesign implementation project, and before that, the management wanted to know the main target of the process redesign, especially across the marketing and production departments. Accordingly, we applied the proposed approach in finding the leverage points in decision making for increasing profit by identifying core factors and core activities.

The application of the proposed method was carried out by two researchers who had knowledge about the proposed method and cognitive map, along with the company's project team, which mainly consisted of members of related departments. Two researchers educated the project team about the procedure and the use of cognitive map, particularly, focusing on the knowledge elicitation of individual department. This study lasted for a month until the business process redesign implementation project started.

Individual Knowledge

Individual knowledge was gathered from the marketing and production departments. To generate a cognitive map for each department, a brainstorming session and interviews with participants from each department were held. Following the discussion and interviews, the participants established the goals for their respective departments. The marketing department set increasing sales as its goal, while the production department decided on improving productivity. Next, we attempted to extract

Figure 3. Individual knowledge models of two departments



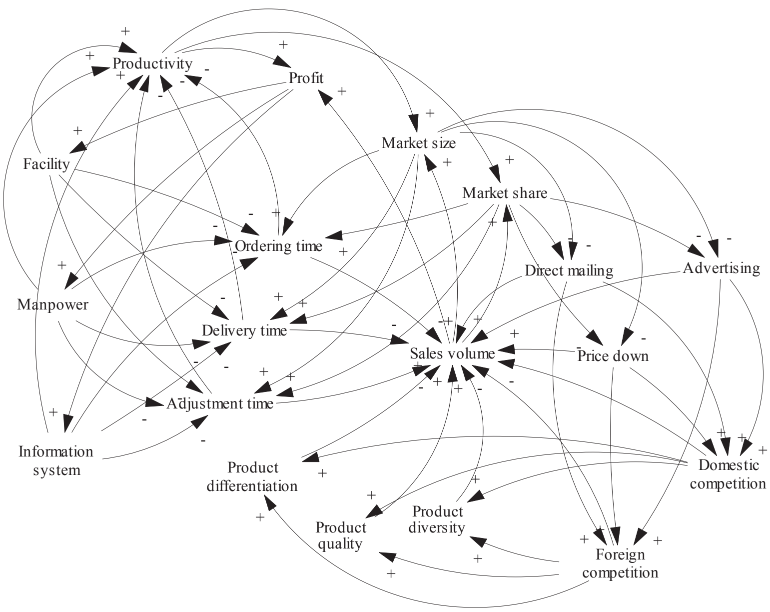
all the causal factors for each department, including business-related activity concepts. The brainstorming technique again was used. When all the causal factors had been listed, they were clustered according to their functional similarity and behavioral homogeneity. Based on these clusters, the relationships between clusters were identified, along with their directions and polarities. A cognitive map was derived from the list of causal factor clusters and the cluster relationships; this was done by replacing clusters with their corresponding causal factors and making appropriate connections among causal factors. Then cognitive maps were generated from the two departments along with the relevant goals, as illustrated in Figure 3.

Organizational Knowledge

Knowledge related to organizational goals is dispersed across a company, and it is kept by the top management, departmental managers, and departmental staff members of the firm. This knowledge is identified and organized through "externalization" and "combination." Although some information or knowledge can be obtained from documents or databases, large portions of knowledge reside in mental models. In our case application, we conducted interviews with the top managers and the middle managers of the two departments to identify partial knowledge. By having these interviews, we could detect and resolve discrepancies between the cognitive maps of the two departments.

Combining the individual knowledge models of the two departments generated the organizational knowledge model as depicted in Figure 4. The synthesizing process revealed organizational knowledge that was

Figure 4. The organizational knowledge model between the two departments



not known explicitly to the departments. The two departments became aware of how elements in one department could affect the other department. For example, efforts to increase market share by the marketing department could lead to increasing ordering time and delivery time, thus resulting in diminished productivity, which is of interest to the production department.

Formulating and Testing the Knowledge Model

The organizational knowledge represented in the cognitive map was analyzed in terms of the causal paths and strengths among the elements to identify the leverage points in decision making. The causal impact paths among the causal factors as well as their values were computed. In this application case, core business activities were identified from the causal impact paths and values matrix, as illustrated in Table 3 (and also in Figure 5).

When increasing profit was considered as a target goal, the two most effective causal factors were identified from the causal impact paths and values matrix (refer to Table 4). One was productivity, which was the most positive causal factor. It represented an opportunity to accomplish the organizational goal because productivity enhancement contributes most to increasing corporate profit. The other one was ordering time, which was the most negative causal factor. It represented a problem for the attainment of the goal because an increase in ordering time undermines profit increases through a decrease in sales volume. The objective was, therefore, to strengthen the positive causal factor ("productivity") and weaken the negative casual factor ("ordering time").

Table 3. Analysis of core business activities

Causal factor		Feedback loops
The most positive impact factor: Productivity	Positive	Path = {Productivity - Profit – Information system - Productivity} Value = +0.52*
	Negative	Path = {Productivity - Market share - Ordering time - Productivity} Value = -0.19*
The most negative impact factor: Ordering time	Positive	Path = {Ordering time - Productivity - Profit - Information system - Ordering time} Value = +0.36*
	Negative	Path = {Ordering time - Sales - Market share - Ordering time} Value = -0.32*

* *Values can be calculated based on the path of feedback loops and the corresponding causal values as follows: +0.52=(+0.67)*(+1.0)*(+0.77); -0.19=(+0.33)*(+0.83)*(-0.70); +0.36=(-0.70)*(+0.67)*(+1.0)*(-0.77); -0.32=(-0.57)*(+0.67)*(+0.83) (refer to Appendix 2).*

As can be seen in Table 3 and Figure 5, the causal factors—productivity and ordering time—possessed *positive* feedback loops of {Productivity–Profit–Information system–Productivity} and {Ordering time–Productivity–Profit–Information system–Ordering time}, respectively. In addition, the two factors possessed *negative* feedback loops of {Productivity–Market share–Ordering time–Productivity} and {Ordering time–Sales–Market share–Ordering time}, respectively. It seems clear that the paths, {Productivity–Profit–Information system} and {Ordering time–Productivity}, were the main drivers that could accelerate an improvement in productivity and a decrease in ordering time. Thus, by designating the above two paths of related activities as core business activities, it would be possible to focus on how to use information technologies in redesigning the processes related to productivity and ordering time.

Decision Support

Based on the above organizational knowledge and consensus, the ordering process was identified as a candidate target process for possible redesign. The existing ordering process depended heavily on manual handling and required the intervention of the sales branches. This resulted in long ordering time and inefficiency in production and delivery. Including a new client-server system in the redesign of the ordering process could significantly reduce total ordering time.

Figure 5. Feedback loops related to the target goal

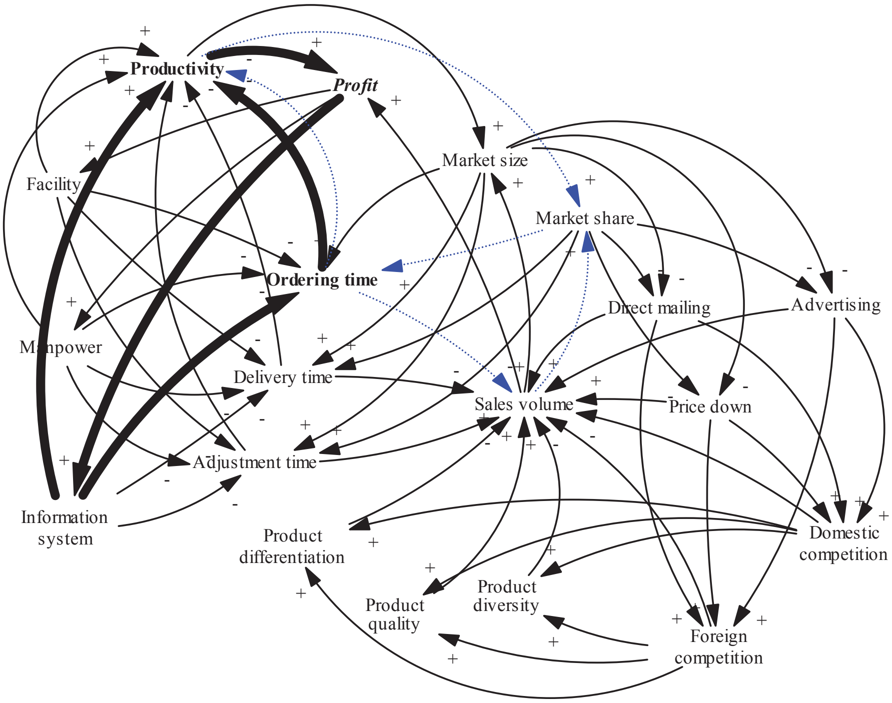


Table 4. Part of causal impact paths and values matrix (causal factor "profit" column)

Cell	Positive		Negative	
(*i, j*)	Value	Path	Value	Path
(01, 01)	+0.516	1- 14- 11- 1	-0.114	1- 14- 15- 2- 19- 15- 11- 1
(02, 01)	+0.330	2- 1	-0.261	2- 19- 15- 11- 1
(03, 01)	+0.026	3- 2- 1	-0.021	3- 2- 19- 15- 11- 1
(04, 01)	+0.198	4- 2- 1	-0.156	4- 2- 19- 15- 11- 1
(05, 01)	+0.160	5- 7- 9- 2- 1	-0.159	5- 6- 2- 1
(06, 01)	+0.175	6- 2- 19- 15- 11- 1	-0.221	6- 2- 1
(07, 01)	+0.211	7- 9- 2- 1	-0.167	7- 9- 2- 19- 15- 11- 1
(08, 01)	+0.056	8- 2- 1	-0.044	8- 2- 19- 15- 11- 1
(09, 01)	+0.254	9- 2- 1	-0.201	9- 2- 19- 15- 11- 1
(10, 01)	+0.020	10- 2- 1	-0.016	10- 2- 19- 15- 11- 1
(11, 01)	+0.670	11- 1	-0.128	11- 19- 15- 11- 1
(12, 01)	+0.114	12- 11- 1	-0.022	12- 11- 19- 15- 11- 1
(13, 01)	+0.080	13- 15- 11- 1	-0.025	13- 15- 2- 19- 15- 11- 1
(14, 01)	+0.516	14- 11- 1	-0.114	14- 15- 2- 19- 15- 11- 1
(15, 01)	+0.149	15- 2- 19- 15- 11- 1	-0.469	15- 11- 1
(16, 01)	+0.026	16- 2- 19- 15- 11- 1	-0.040	16- 11- 1
(17, 01)	+0.086	17- 2- 19- 15- 11- 1	-0.161	17- 11- 1
(18, 01)	+0.025	18- 15- 2- 19- 15- 11- 1	-0.080	18- 15- 11- 1
(19, 01)	+0.138	19- 5- 6- 2- 1	-0.389	19- 15- 11- 1

Note: 1 represents-profit; 2 represents sales amount; 3 represents DM; 4 represents advertising; 5 represents price down; 6 represents domestic competition; 7 represents foreign competition; 8 represents product differentiation; 9 represents product quality; 10 represents product diversity; 11 represents productivity; 12 represents facility; 13 represents manpower; 14 represents information system; 15 represents ordering time; 16 represents delivery time; 17 represents adjustment time; 18 represents market size; and 19 represents market share.

In the redesigned ordering process, every agency could send its orders directly to the factory through the network without the intervention of the sales branches. Reducing the branches' role in order taking was expected to result in shorter ordering time, which in turn was likely to increase efficiency in production and delivery and, in the long run, contribute to profit. In addition to discovering the best decision option, the top management and managers at other levels came to understand the elements involved in the business process, the relationships among them, and the behavioural mechanism of the target business problem.

At the end of the application of the proposed method, the results and insights were presented to the top management of the firm and the two departments. The top management came to understand what factors affected organizational profit and how the factors were related across the two departments. In addition, the management could now perceive why the proposed decision guidelines would be effective. The two departments and the individual employees also could expand their department-constrained knowledge into cross-department knowledge. Thus, the proposed method facilitated understanding of the behavioural mechanism regarding the target managerial problem by linking knowledge integration to decision support.

In summary, the goal in the application case was to identify the decision options to increase profit. For company-level decision making, such as in the application case, knowledge integration (regarding how to increase profit and what factors affect profit) across functional areas is essential. As part of knowledge management, the proposed approach facilitates the identification and integration of partial knowledge (as in Figure 3) into organized knowledge (as in Figure 4). In decision making, there could be several and many decision options. Identifying the best option or core factors is one of the main goals in decision support (as in Figure 5). Thus, the matrix method enabled us to identify the core factors regarding the goal of decision making based on the combined knowledge model. In the case study, the management and the two departments gained newly identified knowledge through our proposed process.

DISCUSSION

Any problem is characterized by its complexity type: detail complexity and dynamic complexity (Senge, 1990; Sterman, 2000). Detail complexity arises when it focuses on the static aspect of a structured problem by highlighting the correctness of selected variables. Dynamic complexity arises when it focuses on the dynamic aspect of an unstructured problem by highlighting the interactions among the variables. Any problem characterized by detail complexity tends to entail mathematical modeling approach to find an optimal solution. In contrast, any problem characterized by dynamic complexity tends to entail the cognitive modeling approach to design a better behaved system by understanding the behavior mechanism. Organizational problems (or business management problems) are characterized by dynamic complexity, tacit knowledge factors, feedback effects over time, and unstructuredness (Sterman, 2001).Organizational problems especially require (tacit and explicit) knowledge gathering and integration across employees and organization units (Argote, McEvily, & Reagans, 2003; King, 2006). In addition, a systematic approach is needed to identify and capture knowledge within the organization (Cai, 2006; Nah, Siau, & Tian, 2005). Based on these needs, this study proposed a knowledge integration approach for organizational decision support by developing a cognitive modeling methodology together with the decision support loop. We believe the developed decision support loop and the methodology (including tasks and relevant methods in each step over the two common stages) is unique compared to other decision support approaches.

The case described in the previous section may be best discussed as an exercise in knowledge conceptualization. During the conceptualization process, the knowledge related to the target problem was identified and structured from the causal relationship perspective using cognitive maps. The analysis enabled decision makers to: (1) trace the basic causes of unexpected outcomes; (2) understand which decision factors had more significant impacts on performance; and (3) make trade-offs between decision alternatives. The reasoning process had effects on both the value of decision factors and the causal relationships.

Our proposed approach is characterized by its learning process and organizational memory. Learning allows individuals to obtain knowledge and insight from the results of experiences, and facilitates the application of this knowledge to future circumstances (Fiol & Lyles, 1985). Organizational learning aims to obtain knowledge, store it in the organizational memory, and revise it by experience; the accumulated organizational knowledge is thus diffused (Huber, 1991; Senge, 1990). Organizational memory refers to "the means by which knowledge from the past [is] brought to bear on present activities, thus resulting in higher or lower levels of organizational effectiveness" (Stein, 1995). Ramesh (1999) suggested the development of organizational memory through the identification of information that should be provided as part of cognitive feedback, together with the interdependencies within this information. Organizations update their respective organizational memories that consist of knowledge through learning. Our proposed approach enables an organization to obtain of previous knowledge from individuals or organizational knowledge models, allows for the creation of new organizational knowledge, and allows for its revision by reasoning and new experiences. The management and teams of an organization can share the collective tacit/explicit knowledge to improve their understanding of the target situation, which will enable them to be more cooperative in their dealings with each other. The organizational knowledge model, thus, plays a role in organizational memory.

Compared to other general decision support approaches, our approach would be more appropriate to the decision-making context with highly constrained tasks involving resource allocation. Highly constrained tasks can be classified as mixed-motive negotiation tasks in which participants have mixed motives to compete and cooperate (McGrath, 1984; Rees & Barkhi, 2001). It is, therefore, important to understand the overview of the system, and this should be shared among participants with respect to how one part of a decision can affect other parts. Decision-making support should aid individuals or subunits in an organization in exchanging information and making coordinated decisions (Barkhi, 2001–2002). The proposed approach enables individuals or subunits in an organization to make decisions consistent with the organizational goals, leading them to collaborate with each other by linking organizational knowledge to decision support.

As part of the proposed approach, the matrix method seeks to provide problem-solving guidelines in a systematic way that is lacking in most cognitive map methods. The merit of our approach is that it quantifies the knowledge represented in the map and identifies core factors and the relationships among them. The identified factors and relationships are new knowledge that comes with the application of our method. Their importance is reflected in the fact that they are the main target for decision making. Therefore, our matrix method plays an important role in the proposed organizational decision support through knowledge integration across organizational units.

Our proposed matrix approach is more appropriate for testing linear problems, but many real-world problems (or systems) are characterized by nonlinearity. The main focus of system dynamics is to conceptualize and test the effect of nonlinearity over time. While our proposed approach captures nonlinearity in structuring a problem, the matrix method has its limitations in testing nonlinearity effects over time. Nevertheless, the limitation can be eased by combining the proposed matrix approach with the typical system dynamics approach. Based on the identified core loop and factors from the matrix approach, we can further test the model (or business problem) with the format of the stock-flow diagram of the system dynamics approach. In the testing, we could consider nonlinearity in the system; and we could validate whether the identified core loop and factors produce real leverage effect in the nonlinear system.

CONCLUSION

The core contribution of our study lies in proposing a methodology for organizational decision support based on knowledge gathering and integration across organization units and people. While most previous research on knowledge management has focused on identifying and sharing knowledge mainly for transaction processing in an organization, this study explains how organizations can apply knowledge management (i.e., knowledge gathering and integration across multiple individuals and organizational units) for organizational decision support. For this, we have developed and proposed the decision support loop. The decision support loop facilitates integrating individual knowledge into organizational knowledge, then formulating and testing it for decision support. For the knowledge representation, formulation, and testing, we used the cognitive modeling method, which enables decision makers to estimate the strength of the impact between causal factors. The generation of alternatives and the testing of those alternatives enable decision makers to appreciate the behavioural mechanism and the inherent structure of the target business problem. The application case showed the validity and usefulness of the proposed method.

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REFERENCES

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly, 25*(1), 107-136.

Argote, L. B., McEvily, B., & Reagans, R. (2003). Introduction of the special issue on managing knowledge in organizations: Creating, retaining, and transferring knowledge. *Management Science, 49*(4), v-viii.

Axelrod, R. (1976). *Structure of decision: The cognitive maps of political elites*. NJ: Princeton University Press.

Barkhi, R. (2001-2002). The effects of decision guidance and problem modelling on group decision-making. *Journal of Management Information Systems, 18*(3), 259-282.

Brown, J. S., & Dugid, P. (1998). Organizing knowledge. *California Management Review, 40*(3), 90-111.

Cai, J., (2006). Knowledge management eithin collaboration processes: A perspective modeling and analyzing methodology. *Journal of Database Management, 17*(1), 33-48.

Davenport, T. H. (1998). *Working knowledge*. MA: Harvard Business School Press.

Davenport., T. H., De Long, D. W., & Beers, M. C. (1998). Successful knowledge management projects. *Sloan Management Review,* 43-57.

Eden, C., & Ackermann, F. (1989). Strategic options development and analysis (SODA)-using a computer to help with the management of strategic vision. In G. Doukidis, F. Land, & G. Miller (Eds.), *Knowledge-based management support systems*. UK: Ellis Horwood.

Eden, C. (1988). Cognitive mapping. *European Journal of Operational Research, 36,* 1-13.

Etzioni, A. (1964). *Modern organizations*. NJ: Prentice-Hall.

Fiol, C. M., & Huff, A. S. (1992). Maps for managers: Where are we? Where do we go from here? *Journal of Management Studies, 29*(3), 267-285.

Fiol, C. M., & Lyles, M. A. (1985). Organizational learning. *Academy of Management Review, 10*(4), 803-813.

Grover, V., & Davenport, T. (2001). General perspectives on knowledge management: Fostering a research agenda. *Journal of Management Information Systems, 18*(1), 5-21.

Hall, R. (1984). The natural logic of management policy making: Its implications for the survival of an organization. *Management Science, 30*(8), 905-927.

Hamner, W. C., Ross, J. & Staw, B. M. (1983). Motivation in organizations: the need for a new direction. In R. M. Steers & L. W. Porter (Eds.), *Motivation & work behaviour* (pp. 52-72). NY: McGraw-Hill.

Hanse, M. T. (2002). Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organization Science, 13*(3), 232-248.

Huber, G.. P. (1991). Organizational learning: The contributing process and the literature. *Organization Science, 2*(1), 88-115.

Kankanhalli, A., Tan, B., & Wei, K. K. (2005). Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly, 29*(1), 113-143.

King, W. R. (2006). The critical role of information processing in creating and effective knowledge organization. *Journal of Database Management, 17*(1), 1-15.

Kwahk, K. Y., & Kim. Y. G.. (1999). Supporting business process redesign using cognitive maps. *Decision Support Systems, 25,* 155-178.

Lee, S., Courtney, J. F., & O'Keefe, R. M. (1992).A system for organizational learning using cognitive maps. *Omega, 20*(1), 23-36

Lee, J. H., & Kim, Y. G.. (2001). A stage model of organizational knowledge management: A latent content analysis. *Expert Systems with Application, 20*(4), 299-311.

Lenz, R. T., & Engledow, J. L. (1986). Environmental analysis: The applicability of current theory. *Strategic Management Journal, 17*(4), 329-346.

McGrath, J. E. (1984). *Groups: Interaction and performance.* NJ: Prentice

Hall.

Nadkarni, S., & Nah, F. F. (2003). Aggregated causal maps: An approach to elicit and aggregate the knowledge of multiple experts. *Communications of the Association for Information Systems, 12,* 406-436.

Nah, F., Siau, K., & Tian, Y. (2005). Knowledge management mechanisms of financial service sites. *Communications of the ACM, 48*(6), 117-123.

Nambisan, S., & Wilemon, D. (2000). Software development and new product development: Potentials for cross-domain knowledge sharing. *IEEE Transactions on Engineering Management, 47*(2), 211-220.

Nilakanta, S., Miller, L. L., & Zhu, D. (2006). Organizational memory management: Technological and research issues. *Journal of Database Management, 17*(1), 85-94.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5*(1), 14-37.

Ramesh, B. (1999). Towards a meta-model for representing organizational memory. *Proceedings of Hawaii International Conference on Systems Science* (pp. 320-329).

Rees, J., & Barkhi, R. (2001). The problem of highly constrained tasks in group decision support systems. *European Journal of Operational Research, 135,* 220-229.

Saaty, T. L. (1980). *The analytic hierarchy process*. NY: McGraw-Hill.

Sambamurthy, V., & Subramanu, M. (2005). Special issue on information technologies and knowledge management. *MIS Quarterly, 29*(2), 193-195.

Senge, P. (1990). *The fifth discipline: The art and practice of the learning organization*. NY: Currency Doubleday.

Siau, K. (2000). Knowledge discovery and an aid to organizational creativity. *Journal of Creative Behaviour, 34*(4), 248-158.

Siau, K., & Tan, X. (2005). Improving the quality of conceptual modelling using cognitive mapping techniques. *Data and Knowledge Engineering, 55*(3), 343-365.

Siau, K., & Tan, X. (2006). Cognitive mapping techniques for user-database interaction. *IEEE Transactions on Professional Communication, 49*(2), 96-108.

Simon, H. (1964). On the concept of organizational goals. *Administrative Science Quarterly, 9,* 1-22.

Smith, G. F. (1989). Defining managerial problems: a framework for prescriptive theorizing. *Management Science, 35*(8), 963-981.

Stein, E.W . (1995). Organizational memory: Review of concepts and recommendations for management. *International Journal of Information Management, 15*(2), 17-32.

Sterman, J. (2000). *Business dynamics: Systems thinking and modelling for a complex world*. NY: McGraw Hill.

Sterman, J. (2001). System dynamics modelling: Tools for learning in a complex world. *California Management Review, 43*(4), 8-25.

Weick, K. E., & Bougon, M. G. (1986). Organizations as cognitive maps. In H. P. Sims & D. A. Gioia (Eds.), *The thinking organization: Dynamics of organizational social cognition* (pp. 103-135). CA: Jossey-Bass.

Xu, Y., Tan, B., & Yang, L. (in press). Who will you ask? An empirical study of interpersonal task information seeking. *Journal of the American*

Society for Information Science and Technology.

Zhang, W. R., Wang, W., & King, R. S. (1994). A-pool: An agent-oriented open system shell for distributed decision process modeling. *Journal of Organizational Computing, 4*(2), 127-154.

APPENDIX

1. Simplified algorithm for computing causal impact paths and value s

Initialization

Set X_{ij} such as

$+p_{ij} = \{i, j\}$, $-p_{ij} = \{\phi\}$, $+v_{ij} = u_{ij}$, $-v_{ij} = 0$, If $u_{ij} > 0$

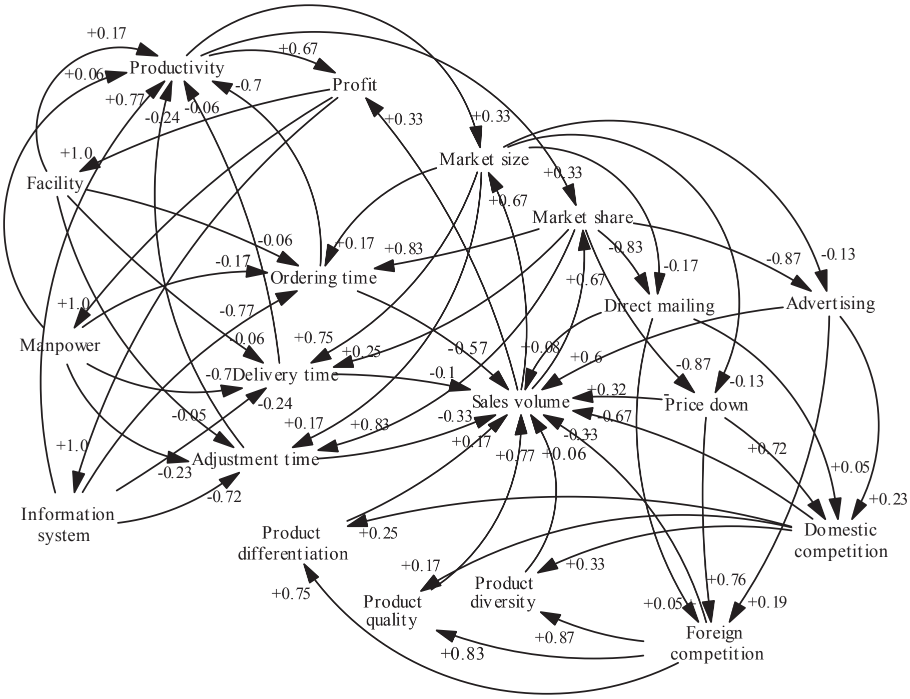
$+p_{ij} = \{\phi\}$, $-p_{ij} = \{i, j\}$, $+v_{ij} = 0$, $-v_{ij} = u_{ij}$, If $u_{ij} < 0$

$+p_{ij} = \{\phi\}$, $-p_{ij} = \{\phi\}$, $+v_{ij} = 0$, $-v_{ij} = 0$, If $u_{ij} = 0$

Main procedure

```
Do while being improvement
   For i = 1 To n
       For j = 1 To n
           For k = 1 To n
               Read -v_ij, +v_ij, -v_ik, +v_ik, -v_kj, +v_kj
               If -v_ij > (-v_ik) * (+v_kj)
                   Set -v_ij = (-v_ik) * (+v_kj)
                   Set -p_ij = (-p_ik) ∪ (+p_kj)
               End If
               If -v_ij > (+v_ik) * (-v_kj)
                   Set -v_ij = (+v_ik) * (-v_kj)
                   Set -p_ij = (+p_ik) ∪ (-p_kj)
               End If
               If +v_ij < (+v_ik) * (+v_kj)
                   Set +v_ij = (+v_ik) * (+v_kj)
                   Set +p_ij = (+p_ik) ∪ (+p_kj)
               End If
               If +v_ij < (-v_ik) * (-v_kj)
                   Set +v_ij = (-v_ik) * (-v_kj)
                   Set +p_ij = (-p_ik) ∪ (-p_kj)
               End If
           Next k
       Next j
   Next i
Loop
```

2. Organizational knowledge model with causal values



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