Knowledge Management in Decision Making: Instance-Based Cognitive Mapping

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Abstract

Knowledge management deals with explicit knowledge and tacit (or implicit) knowledge. One form of tacit knowledge is an individual's mental model—a hypothetical knowledge structure that integrates the ideas, assumptions, relationships, insights, facts, and misconceptions that together shape the way an individual views and interacts with reality. The purpose of this paper is to explore these mental models, why they need to be made explicit, and how such externalization can be accomplished. Specifically, after a review of the mental model theory, we propose a new technique for determining an individual's mental model based on his/her decisions in several selected situations within a specific decision domain.

1. Introduction

Knowledge management deals with two forms of knowledge: explicit knowledge and tacit (or implicit) knowledge. Explicit knowledge is defined as knowledge that can be expressed formally and can, therefore, be easily communicated or diffused throughout an organization. In decision making, explicit knowledge may include trade journal articles, executive reports, verbal communications, project status reports, etc. On the other hand, tacit knowledge consists of subjective expertise, relationships, assumptions, insights, and intuitions that an individual develops from being immersed in an activity or profession for an extended period of time. Tacit knowledge is often integrated and stored in the form of mental models that become so ingrained in the decision maker's mind that they are instinctive and thus not easily verbalized or communicated. These mental models are critical in decision making since they are the primary source of the decision alternatives, the relative evaluations of these alternatives, and the resulting decision.

Nonaka and Takeuchi [19] view tacit knowledge and explicit knowledge as complementary entities, and suggest that there is an organizational knowledge spiral, beginning and ending with the knowledge worker/decision maker that can create, amplify and crystallize new organizational knowledge. This knowledge spiral consists of sharing tacit knowledge between individuals (socialization), converting tacit knowledge into explicit knowledge (externalization), integrating this explicit knowledge with other explicit knowledge (combination), and forming, updating, and/or enhancing the mental model held in the minds of the decision makers (internalization). The knowledge spiral is driven by two sets of dynamics: converting tacit knowledge (i.e., the decision maker's mental model) into explicit knowledge so that it can be more easily shared with and analyzed by others; and moving that explicit knowledge from the individual level to the group, organizational, and interorganizational levels [19]. Arguably, the most critical (and difficult) part of the knowledge spiral is the externalization of the decision maker's mental model.

The purpose of this paper is to explore mental models, why they need to be made explicit, and how such externalization can be accomplished. The paper is organized as follows. We review mental model theory and cognitive mapping theory in Sections 2 and 3, respectively. In Section 4 we describe existing cognitive mapping techniques and follow with a discussion of their limitations in Section 5. In Section 6, we propose instance-based cognitive mapping (ICM) as a new technique for discovering an individual's mental model. Section 7 contains an example application of ICM and some preliminary experimental results from experimentation with it. Finally, in Section 8 we present our conclusions and propose several avenues for future research.

2. Mental model theory

Mental models are tacit, hypothetical knowledge structures that integrate the ideas, practices, assumptions, beliefs, relationships, insights, facts and misconceptions that together shape the way an individual views and interacts with reality [12]. Once formed, mental models provide the decision maker with a way to process data and information within a

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decision domain, reason about the problem, simulate the outcome of various alternatives, and evaluate those potential outcomes with respect to an appropriate set of criteria [11].

Mental models can be divided into two co-existing types: "theories-in-use" which are the mental models that are implicit in the decisions or actions, and "espoused theories" which are the (rational, politically correct) mental models that the individual uses to articulate or justify a given decision or action These two types of mental models may differ significantly for the same decision or action; i.e., the latter provides the rational explanation of the former, but may or may not provide a faithful representation of it. In fact, the discrepancies are so prominent that Argyris and Schön [1] (pp. 13-14) state that you cannot ask an individual to describe his/her "theory-in-use" (after all, it is tacit knowledge); rather, you can only hypothesize it and test it by observing actual actions

One of the primary advantages of mental models is that they provide a simplified framework used by the individual to interpret the massive amount of stimuli and data constantly being processed by the senses; e.g., if we're looking for a MacDonald's restaurant, our mental model of the "golden arches" tends to filter out the logos of other restaurants, as well as other places of business, in the search for the logo of interest. Another advantage is that mental models are "executable;" e.g., if there are multiple routes to the nearest MacDonald's, we can mentally trace each of the different routes to determine which is the fastest. A third advantage is that the interconnecting associations between mental models allow thoughts and ideas to follow one another logically and sequentially; i.e., when one concept in one mental model is triggered, that concept can trigger other, related concepts in other mental models, bringing them into awareness.

Unfortunately, there are also several disadvantages associated with mental models. Arguably, the most subtle disadvantage is that mental models introduce significant biases in the processing of new information. That is, information that supports or reinforces an existing mental model is readily accepted and stored, whereas information that is contradictory to an existing mental model may be stored in relative isolation (as inert knowledge), and later discarded without being incorporated into the individual's mental structure [2, 3].

Several additional problems and pitfalls sometimes fostered by mental models are illustrated by the following scenario.

> In the early 1990's, the Marketing VP of a large refiner/marketer of petroleum products was directed to develop a strategy that would significantly increase gasoline profits during the next quarter. The VP responded with a two-pronged plan: 1) institute an aggressive pricing policy, setting prices two cents below the competition, but staying above a pricing floor calculated by allocating the crude cost plus refining, transportation and handling costs, and 2) offer a free coffee mug (adorned with the company logo) with every fill-up. Upon implementation, the results proved to be disastrous. Profits plummeted by 20% and customers regularly refused the free mugs, leaving the company with a warehouse full of unused promotional merchandise.

Was the Marketing VP incompetent? No, but his mental model of profit improvement was seriously flawed in at least three ways. First, his mental model was outdated, since it was based on a 1960's mental model that the VP had developed and successfully implemented early in his career (and had never forgotten – or updated!). Second, his model contained erroneous assumptions concerning the reaction of the competitors; specifically, the competition quickly dropped their prices, resulting in a downward spiral to our VP's pricing floor. And third, his pricing model was incomplete since his floor price did not include the financial cost of inventories (roughly 3 cents/gallon) resulting in a floor price that did not cover all the variable cost of sales; i.e., the more gasoline the company sold, the more money it lost.

Given that mental models are tacit, and need to be converted to explicit knowledge so that they can be examined, analyzed, compared, updated, shared and enhanced, what methods can be used to extract them and make them explicit; i.e., in the terms of Nonaka's [19] knowledge spiral, how can they be externalized?

3. Tacit to explicit knowledge externalization: cognitive mapping theory

One way to externalize the tacit knowledge of a mental model is through the extended theory of cognitive mapping. In this context, cognitive mapping is defined as the process of capturing and describing the important features of an individual's mental model in a domain-specific arena, including the assumptions, key factors (conceptual, logical, physical) and their interrelationships (temporal, causal, spatial) [13]. Whereas early research in cognitive mapping dealt primarily with spatial knowledge (how far X was from Y and in what direction) [27], the theory and techniques have been extended to include any important object and concept, and to code the temporal and causal, as well as the spatial relationships. However, the analogy with geographical maps is still revealing, as is illustrated by the following map story.

> A small Hungarian detachment was on military maneuvers in the Alps. Their young lieutenant sent a reconnaissance unit out into the icy wilderness just as it began to snow. It snowed for two days, and the unit did not return. The lieutenant feared that he had dispatched his people to their deaths, but on the third day the unit came back. Where had they been? How had they made their way?
>
> Yes, they said, we considered ourselves lost and waited for the end, but then one of us found a map in his pocket. That calmed us down. We pitched camp, lasted out the snowstorm, and then with the map we found our bearings. And here we are. The lieutenant took a good look at this map and discovered, to his astonishment, that it was a map of the Pyrenees. [29].

The moral of the map story, (and it applies equally well to decision making) is that, if you're lost, almost any map (or mental model) will help. First, keeping the mental model (map) hidden away in the mind (pocket) is OK, but it is much more useful if brought out and shared with others; this is what cognitive mapping is all about. Second, once externalized, the mental model will tend to calm the decision maker(s) as the map did the lost soldiers, by providing a (perhaps false) sense of security and direction, and start the decision making process. And finally, even though the existing mental model may initially color perceptions (i.e., we tend to see what we expect to see) eventually, as discrepancies between the mental model and new experiences accumulate, a perceptive decision maker will look for new patterns that explain the new experiences, modifying the existing mental model or, if the discrepancies are too great, replacing it with a new model based on the observed patterns. But it is the existing mental model that calls attention to the discrepancies between old and new experiences; i.e., it takes a mental model to make a mental model because one points out differences that are mapped into the other. Mental models "provide a frame, albeit a flawed (simplified) one, within which experience can be understood. Parts of the mental model (map) confirm that experience, but more important, parts are discrepant with it" [29]. Discrepancies between existing mental models and current experiences stand out because comparison is made possible.

Thus, there are at least two justifications for capturing the decision maker's (tacit) mental model and making it explicit. First, the assumptions, key factors, concepts and relationships can be reviewed, analyzed, and questioned. This is especially important with interdisciplinary teams whose mental models may differ, and with novel and complex problems that may require the selection and integration of several different mental models. Second, new and/or contradictory patterns and information can be compared with the existing mental model and presented to the decision maker in terms of his/her own mental model, increasing the chances that s/he will incorporate this new information. This is the implementation of the "it takes a mental model to make a mental model" concept referred to by Weick [29] above. The latter is important since information that doesn't fit into an existing mental model may be rejected out of hand, or at best filed away in a different part of the brain, given less and less importance, and eventually discarded [3].

4. Cognitive mapping techniques: a taxonomy

Current cognitive mapping techniques span a wide variety of assumptions, inputs, processing, and output formats, but can be divided into three basic types: word-based techniques, graph-based techniques, and frame-based techniques. The word-based techniques assume that a person's, or organization's, mental model can be inferred from what they say or write. So the map maker searches for clusters of frequently used, and related, key words or concepts in the speech or text as indicators of the key components of the underlying mental model(s) [6]. For example, a corporate executive whose speeches contain references to "inventories" and "profits" in close and frequent proximity may hold the mental model that "managing working capital is a key to profitability," a valid model in certain high-volume, low margin industries such as petroleum products marketing. If text data mining algorithms (e.g., CRYSTAL [25], AutoSlog [23]) are used, this semantic mapping technique can be relatively fast, efficient, and free of researcher interpretation and bias [9]. Further, the input to the text mining software is relatively easy to find, coming from annual reports, corporate documents, executives' speeches, etc.

Graph-based cognitive mapping assumes that causal or conceptual associations and/or arguments provide understanding about how an individual's knowledge is organized in a mental model, and can provide the means of choice among alternatives in the individual's decision making. Map makers thus conduct and transcribe extensive open-ended interviews, and extract from the resulting interview transcripts the pertinent concepts, arguments, and relationships. Analysts use nodes to represent the concepts and connecting arcs to represent influence, causality and/or system dynamics between the nodes. For example, in causal diagrams, the direction of causality or influence between two concepts is indicated by an arrow which can be signed to show the direction of causality; i.e., a minus sign on an arrow linking concepts A and B indicates that increases in concept A reduces the value in concept B. The most popular graph-based mapping techniques are influence diagrams [4], free card-sorting [16], argument mapping [17], conceptual content cognitive mapping [14], and causal maps [18, 22]. Also included in this group of mapping techniques are dichotomized hierarchical charts and decision trees (with the associated production rules of expert systems). The primary advantages of graph-based mapping include the diversity of potential applications and the ability of decision makers to explore their own knowledge structures during the interview process [14].

Frame-based cognitive mapping assumes that an individual's perception of a given event is greatly influenced by his/her previous experiences which form a hierarchical framework within which decisions are made. For example, a corporate Vice President might analyze competing capital projects in terms of the nested expectations of a capital budget meeting schema shown in Figure 1. In this case, each project is represented by a frame which includes a set of slots with attributes that describe the project, with each slot containing one or more facets that describe some knowledge or procedure about the attribute in the slot. The individual's schema (including frames, slots and facets) for a specific decision making environment can theoretically be tapped/explored via extensive interviews and interpretation by experienced researchers; e.g., by using a process called "semiotics" [7]. The primary advantages of frame-based cognitive mapping include its intuitive appeal (all new analyses and decisions are structured by previous experiences), and its ability to show commonalities among schemas and frames held by individuals within an organization, an important trait in coordinated decision making environments.

5. Limitations of current cognitive mapping techniques

There are several limitations of current cognitive mapping techniques. With respect to proximity-based mapping techniques, frequency of word use may or may not indicate saliency or importance, textual proximity of two concepts may or may not indicate mental association of those concepts, and word use may vary significantly within different settings (formal speeches, written communications, company annual reports, etc.) [9].

With respect to both graph-based and frame-based mapping techniques, the open-ended interviews used in these techniques are very time-consuming, both for the decision maker and the interviewer, and require a highly trained interviewer. Further the linkages between concepts are usually monotonic without time delays [8]; and for causal maps, there is no way to indicate uncertainty or fuzziness in the relationships. In addition, the interview analyses from these mapping techniques can be significantly influenced by the investigator's bias; e.g., outside observers suggest that frame-based mapping relies on an *a priori* value schema, a foundation that may skew interpretations of the data as they are fitted to a schema the researcher already has in mind [9] (p. 40). Finally, all of these mapping techniques are qualitative in nature, providing little or no quantitative conclusions, and only indirectly measuring what the executive can be expected to do in a decision making situation.

What is needed is a cognitive mapping technique that is efficient, can be automated (i.e., computerized), is less subjective to interviewer bias, is more directly related to actual decisions, and is more quantitative in nature, providing a valid estimation of the executive's mental model in a specific decision making environment. Such a mapping technique, called instance-based cognitive mapping, is proposed and explored in the following sections.

6. Instance-based cognitive mapping

Instance-based cognitive mapping (ICM) is based on significantly different assumptions when compared to the techniques described in the previous section. Specifically, ICM makes the following assumptions:

1) a decision maker usually cannot describe his/her own mental model; rather, it can only be hypothesized and tested by observing actual decisions or actions [1];

2) within a specific domain, a decision maker relies on certain key factors in evaluating decision alternatives; different values for one or more of these key factors lead to different decisions;

3) when a decision maker is presented with a decision situation within a specific problem domain (i.e., a decision instance), s/he determines the appropriate values of key factors; the decision maker then runs his/her mental model to evaluate the

- MEETING
  - - Place
  - - Day
  - - Time
  - CAPITAL BUDGET MEETING
    - - CEO
    - - Executive VPs
    - - Other attendees
    - PROJECTS
      - Capital ($MM) Available
      - Project rankings by IRR
      - Project earnings risks
      - PROJECT CHAMPIONS
        - Name
        - Forecasting tendency (pessimistic/optimistic)
        - Forecasting technique

Figure 1. Frame-based structure of capital budgeting meeting

alternatives, estimate potential outcomes, and make the best decision;

4) inductive analysis of multiple decisions made by a single decision maker in a specific problem domain can be used to derive a mathematical representation of his/her mental model in that domain; this derived model will be a function of his/her key factors, and will *explicitly* relate how the decision maker *implicitly* uses and weighs the key factors in making the decision.

ICM defines an instance as a set of values assigned to key factors associated in a decision domain. For example, in approving bank loans, there may be several key factors that could collectively indicate the probability of future default, including the applicant's net worth, annual income, current mortgage payments, home equity, credit card balances, and the amount of the requested loan. In a specific loan application, the key factors might be $50,000, $65,000/year, $1,500/month, $15,000, $3,500, and $75,000, respectively. Based on these key factor values, the decision maker would use his/her mental model to calculate the probability of default for a $75,000 education loan.

ICM is actually a multi-step process that begins by delineating the decision domain and generating a set of potential factors for making decisions in that domain. These potential factors may be generated from several sources; e.g., by experts within the firm, by external consultants, and from industry journal articles. From this set of potential key factors the researcher builds a set of 10-20 instances (perhaps from historical case files) that are representative of the decision space, with each instance containing appropriate values of the factors, but without decision outcomes; e.g., a set of 15 loan applications. The instances are then presented, individually or as a group, to the decision maker who is asked to make an appropriate decision in each instance, basing that decision on what s/he considers to be key factors, the relative values of those key factors, and his/her mental model. The resulting decision for each instance is stored and checked for decision inconsistencies; any inconsistent decision(s) are pointed out to the decision maker, including comparisons with other instances to highlight the inconsistency, and the decision maker is requested to reconsider the decision and correct the inconsistency. Upon completion, the set of instances, including both the key factor values and the decisions, are input to the ICM system featuring the Group Method of Data Handling (GMDH) algorithm for processing. GMDH is an inductive self-organizing hybrid of statistical analysis and neural networks that employs a multilayered cascading network of interconnected nodes to model linear and nonlinear relationships [10, 24]. The output is an additive model of linear and nonlinear multinomial terms that explain the variations in the instance decisions based on variations in the key factors values. That is, it produces a mathematical representation of the decision maker's mental model based on the decisions s/he made in the instances presented.

Note that in the procedure described above, the decision maker may implicitly or explicitly select any subset of the factors presented in each instance based on his/her mental model; e.g., if values for factors A, B, C, and D are included in each instance, and the decision maker thinks that only factors A and C are important, then s/he specifies the decision based on only the values of A and C, ignoring B and D values completely. The GMDH algorithm provides several advantages in this application over competing algorithms such as linear or nonlinear regression and neural networks. These advantages include: 1) GMDH is self-organizing and, as such, requires no prior knowledge of which factors are key and no pre-established set of multinomials, 2) in complicated models, GMDH requires a smaller set of instances when compared to standard regressions, 3) GMDH makes no assumptions with respect to linearity or continuity of the solution values or of normality of residuals, and 4) chances of over fitting with GMDH are significantly less than that with neural networks or other inductive learning techniques [21].

In evaluating cognitive mapping techniques, Kearney and Kaplan [14] specify six essential requirements for good mapping techniques; specifically, a cognitive mapping should: 1) focus on the content of the individual's own knowledge structure, specifically those key factors that the individual considers important in the decision domain; 2) ensure that the researcher's ideas and biases do not unduly influence the cognitive mapping process or results, 3) capture important relationships among the individual's key factors, 4) provide for self-analysis of one's own mental models, 5) be relatively time- and cost-efficient without undue mental strain on the decision maker, and 6) be applicable to a wide variety of situations.

Given that the decision maker can ignore any irrelevant factors presented in the case, ICM allows the decision maker to focus solely on those key factors in his/her mental model when specifying the decision. In addition, the self-organizing characteristics of GMDH eliminate any researcher bias that might exist in other (interview-based) mapping techniques; i.e., GMDH independently determines the exponents and coefficients of the decision maker's key factors, while capturing the important mathematical interrelationships among these factors. Also, ICM provides the decision maker potential self-analysis of his/her own mental model both in the consistency checks and corrections, as well as the final mathematical representation of his/her mental model. Further, ICM is significantly more time- and cost-efficient than any interview-based mapping technique, not only in terms of the decision maker's time, but also in terms of the interviewer's and analyst's time. And finally, since instances can be designed to represent most decision making situations, ICM is widely applicable to many different decision domains.

7. A sample application of ICM

As an example of the application of ICM to a business problem, assume the decision domain is that of the classical warehouse location problem in a new market area that includes thirteen cities, all located in central Texas, with a single source of supply in Los Angeles. The problem is to determine the best number of warehouses required to serve the marketing cities at minimum overall cost; there must be at least one warehouse and no more than thirteen warehouses, with each warehouse located in one of the demand cities. Each warehouse built has sufficient throughput capacity to serve the total market demand throughout the area. Further, assume that a group of internal and external consultants have generated a set of three factors that might affect the best number of warehouses: 1) the forecasted demand, d, at each of the thirteen cities (assumed to be the same for each of the thirteen cities), 2) the fixed building costs, f, of each warehouse (assumed to be the same at each potential warehouse locations), and 3) the unit transportation costs, t, from the warehouse to each demand city (to be multiplied by the actual distance from the closest warehouse location to the demand city). The consultants also generate a practical range of values for each of the factors, and from those ranges, generate a set of 17 decision making instances (Table 1). These 17 instances, consisting only of the three columns labeled d, t, and f, are presented to four decision makers via the ICM system. Each decision maker then enters a decision for each case into the ICM system. In the experiment detailed here the ICM system employed the "Find Laws" algorithm of the commercially available PolyAnalyst software [15].

The first decision maker is a very consistent and logical individual whose mental model suggests that all three factors are important; i.e., d, t, and f. Specifically, this decision maker thinks that the best number of warehouses is directly proportional to forecasted demand, d, and unit transportation costs, t, but indirectly proportional to fixed building costs, f. She makes the instance decisions indicated in the column labeled DM#1 in Table 1. After checking for inconsistencies (none exist), the ICM system uses the 17 instances along with the corresponding instance decisions to determine that the mathematical representation of this decision maker's mental model is $n = 706.9\, d * t / f$, where n is the number of warehouses; an associated R^2 of 99.2% indicates the high level of consistency in the decisions. Note that the ICM system required no *a priori* knowledge of which factors were key; neither did it require prior knowledge of any relationships between these key factors (e.g., n is inversely proportional to one or more factors). Rather, the GMDH algorithm generated the mathematical model based only on the three input factors and the instance decisions represented in the DM#1 column. That is, the ICM is basically independent of any potential researcher bias.

The second decision maker selects the same key factors (*d*, *t*, and *f*), but is a bit inconsistent in his application of the values of these factors to one of the instances (the last instance in Table 1, column DM#2). The mathematical expression of this decision maker's mental model based on all 17 instances is $n = 633.3d * t / f$ with a corresponding R^2 value of 65%.

An inconsistency such as the one displayed by DM#2 in instance 17 could be discovered either by analyzing a plot of instance decisions as a function of the factor values, or by using a version of Wagner's [28] "all save one" algorithm in which the GMDH algorithm is repeatedly run with only 16 of the 17 instances, excluding a different instance (row) in each different run, and comparing the results. A result with a significantly higher value for R^2 and/or a significantly less complex mathematical model for *n* would indicate the inconsistent decision had been excluded. The inconsistency would then be pointed out to the decision maker for reconsideration and correction. For example, when the "all save one" process was applied to this set of instance decisions (Table 1, column DM#2), R^2 varied from 53% to 65% when the inconsistent instance (17) was included; but R^2 jumped to 99.0% when the inconsistent instance was excluded. The mathematical representation of DM#2's mental model based on only instances 1 − 16 is given by $n = 704.1\, d * t / f$.

The third decision maker (DM#3 in Table 1) is again very consistent, but implicitly uses only two factors to make his decisions; specifically, demand, *d*, and fixed building costs, *f*. After specifying decisions in the 17 instances based on his tacit mental model, the ICM system determines that his mental model is $n = 14.9 * d / f$, with R^2 equal to 98.7%. Note that, even though neither the researcher nor the ICM system has *a priori* knowledge of the decision maker's mental model, the GMDH algorithm generates the appropriate mathematical representation of the mental model, based solely on the factor values and the instance decisions made by the decision maker. That is, *t* was algorithmically omitted by GMDH.

The fourth decision maker, perhaps trained by the previous individual, shares the same implicit mental model, but, perhaps being less experienced, is less consistent in applying it. She generates the decisions labeled DM#4 in Table 1. In this case, ICM generates the same mathematical equivalent of the mental model as for the previous decision maker, $n = 15.0\ d / f$, but predictably, R2 drops to 58%. This suggests that

Table 1. Instance key factor values and decision makers' corresponding decisions

Instance Number	*d (millions)*	*f (million $)*	*t*	DM#1	DM#2	DM#3	DM#4
1	4.1	15.0	0.01	2	2	4	6
2	1.0	6.0	0.02	2	2	3	1
3	4.1	9.0	0.01	3	3	7	5
4	1.8	8.0	0.02	3	3	3	4
5	7.2	15.0	0.01	3	3	7	9
6	1.8	8.0	0.03	5	5	3	5
7	1.0	3.0	0.02	5	5	5	4
8	4.5	11.0	0.02	6	6	6	5
9	1.0	6.0	0.05	6	6	3	5
10	1.8	9.0	0.05	7	7	3	5
11	1.8	8.5	0.05	7	7	3	4
12	4.1	15.0	0.04	8	8	4	2
13	5.0	13.0	0.03	8	8	6	4
14	1.8	8.0	0.05	8	8	3	4
15	4.5	11.0	0.03	9	9	6	5
16	7.2	9.0	0.02	11	11	12	12
17	1.0	3.0	0.05	12	5	5	7
		PolyAnalyst's Hypothesized Model for *n**		$706.9d*t/f$	$633.3d*t/f$	$14.9d/f$	$15.0d/f$
			R^2	99.2%	65.0%	98.7%	58.0%

the system is relatively stable even in light of 15 – 20% inconsistencies on the part of the decision maker.

8. Conclusions and future research

Mental models are tacit, hypothetical knowledge structures that form the basis of an individual's decision making. However, it is important to convert tacit mental models to explicit knowledge so that the knowledge can be shared with others, and moved from the individual level to the group, organizational and interorganizational levels; this is the basis of the dynamics of organization knowledge creation [19].
The ICM system described herein provides a unique and efficient method for mental model externalization that is based directly on the decisions that an individual makes, requires no prior knowledge of the individual's mental model, and is independent of researcher bias.

Of course, ICM is limited to those decisions for which you can identify both key factors and a valid, estimated, or predicted range of values for each key factor; i.e., one must be able to generate decision instances that make sense. Thus, ICM can be applied to almost all structured and semi-structured decisions, and with a bit of creativity, to many unstructured decisions.

There are several possible avenues for future research using ICM as a tacit-to-explicit knowledge converter. One would be to empirically test the validity of ICM using both experienced and novice decision makers. Such testing could include the sequential application of ICM, immediately followed by a graph-based cognitive mapping technique such as causal mapping to verify that the two techniques generate the same or consistent cognitive maps for the same individual in the same decision making domain. Other empirical investigations might attempt to test for within-subject variability; for example, whether a different day or time may result in a different mental model for the same decision.

Another research direction could address the other end of the knowledge creation spiral, the explicit to implicit knowledge internalization; i.e., the enhancement or updating of an individuals mental model based on new or additional explicit knowledge. Perkins theory of understanding [20, 26] suggests that comparison of an individual's mental model and an expert's mental model could be made. The comparison would include several different types of arguments (evaluative, simple explanatory and deep explanatory arguments) on how the two mental models differ and why one is superior to the other. A potentially interesting empirical test along this line, especially applicable to model-based decision support systems, might include extracting a novice decision maker's mental model in some decision making environment, comparing it to an expert's mental model or a simplified mathematical model [24], generating arguments concerning why the expert's model or the simplified mathematical model is superior, feeding these arguments back to the novice decision maker in an attempt to change and improve his/her mental model, and then re-testing the novice decision maker to determine whether his/her revised mental model produces better decisions. Such a research thrust, based on the lens model [5] would provide a missing link in the current research.

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