Expert Systems with Applications 27 (2004) 143–158

Expert Systems with Applications

www.elsevier.com/locate/eswa

Knowledge based decision making on higher level strategic concerns: system dynamics approach

Nam-Hong Yim[a,*], Soung-Hie Kim[a,1], Hee-Woong Kim[b,2], Kee-Young Kwahk[c,3]

[a]*KAIST Graduate School of Management, 207-43, Chonyangri2-dong, Dongdaemoon-gu, Seoul 130-722, South Korea*
[b]*Department of Information Systems, National University of Singapore, 3 Science Drive 2, Singapore 117543*
[c]*Department of Management Information Systems, Keimyung University, 1000, Sindang-Dong, Dalseo-Gu, Daegu 704-701, South Korea*

Abstract

In recognizing knowledge as a new resource in gaining organizational competitiveness, knowledge management suggests a method in managing and applying knowledge for improving organizational performance. Much knowledge management research has focused on identifying, storing, and disseminating process related knowledge in an organized manner. Applying knowledge to decision making has a significant impact on organizational performance than solely processing transactions for knowledge management. In this research, we suggest a method of knowledge-based decision-making using system dynamics, with an emphasis to strategic concerns. The proposed method transforms individual mental models into explicit knowledge by translating partial and implicit knowledge into an integrated knowledge model. The scenario-based test of the organized knowledge model enables decision-makers to understand the structure of the target problem and identify its basic cause, which facilitates effective decision-making. This method facilitates the linkage between knowledge management initiatives and achieving strategic goals and objectives of an organization.

Keywords: Knowledge management; Naturalistic decision making; System dynamics

1. Introduction

Faced with uncertain and unpredictable business environments, organizations have paid attention to developing knowledge management systems that can provide the basis for future sustainability and competence (Malhotra, 2001). Knowledge management (KM) can be defined as uncovering and managing various levels of knowledge from individuals, teams, and organizations in order to improve performance (Davenport, 1998; Nonaka, 1994). The majority of previous methods in KM have been focused on frameworks for embodying KM effectively and comprehensively (Gold, Malhotra, & Segars, 2001; Liebowitz et al., 2001; Wiig, 1997), with an emphasis on the relation to business processes and performance (Davenport, 1998; Grant, 1996; Kim, Yu, & Lee, 2003), and on gaining competitive advantage (Nonaka, 1994; Teece, 1998a,b). Where knowledge elicitation is the main concern (Ford & Sterman, 1998), decisions in organizational systems generally rely not necessarily solely on the individual, but also on experts working in the specific field. Because of their nature, decisions made within the organization are supported by a larger knowledge base, with more experience and from varying views (Skraba et al., 2003). A real challenge is to capture, control, and develop working knowledge or interpretation and integration of both the internal and external environments of the firm (Bennett, 1998). Organizations need to be smart, agile, and responsive to fast-changing environments. They need to respond and make smart decisions at ever-increasing speed, even as the unintended consequences of speedy decisions flare up in a nanosecond and keep leaders focused only on fire-fighting (Wheatley, 2001).

Grant (1996) identifies three primary mechanisms for the integration of knowledge to create organization capability: directives, organizational routines, and self-contained task teams. In situations in which task uncertainty and

* Corresponding author. Tel.: +82-11-224-7220; fax: +82-2-958-3210.
E-mail addresses: nhyim@kgsm.kaist.ac.kr (N.-H. Yim); seekim@kgsm.kaist.ac.kr (S.-H. Kim); kimhw@comp.nus.edu.sg (H.-W. Kim); kwahk@kmu.ac.kr (K.-Y. Kwahk).
[1] Tel.: +82-11-224-7220; fax: +82-2-958-3210.
[2] Tel.: +65-6874-4867; fax: +65-6779-4580.
[3] Tel.: +82-53-580-6416; fax: +82-53-580-6364.

0957-4174/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2003.12.019

complexity prevent the specification of directives and organizational routines, teams of individuals with prerequisite knowledge and specialty are formed for problem solving (Alavi & Leidner, 2001). A significant amount of knowledge application research has been focused on the directive and organizational routines' mechanisms, but there has been less research on the mechanism of self-contained task teams in the application of knowledge to decision making by top executive management. Effective KM, based on knowledge, should be able to support the core tasks of business management, namely that of decision-making and strategic planning. The problems of decision making in complex dynamic environments have also been examined by others, for example by Sterman (1989, 1994), whose key finding was that human performance in complex systems is poor relative to normative standards.

The focus of our research is to develop a method of knowledge-based decision making (KBDM) for application to business management problems. Business management problems are characterized by dynamic complexity, tacit knowledge factors, feedback effects over time, and unstructuredness (Sterman, 2001). The KBDM method commences with defining management problems that inherent to functional areas. Its application enables us to structure the target problem by integrating partial knowledge across functional areas. The structured problem, which is conceptualized within the integrated knowledge model, is then transformed into a simulation model. The simulation approach based on the model facilitates business decision support.

The structure of this paper is as follows: Section 2 reviews previous research on the concept of knowledge, KM and knowledge based decision making, then suggests a taxonomy of knowledge and characteristics of KM at each organizational level. In Section 3, we will introduce system dynamics (SD) (Forrester, 1961; Senge & Sterman, 1992) as a tool for knowledge-based decision making. Section 4 discusses our empirical research, and reviews decision environments and KBDM. Section 5 compares an SD approach with other decision-making and KM methods. In Section 6, an application case of a telecommunications company will be introduced to evaluate the validity of utilizing KBDM as a KM method. Section 7 compares KBDM with other models and frameworks. Lastly, Section 8 will draw conclusions through a discussion on research results and their limitations.

2. Literature review on knowledge based decision making

2.1. Knowledge

Ackoff and Emory (1972) define knowledge as 'awareness of the efficiency and effectiveness of different action in producing outcomes based on experience' Meantime, Nonaka (1994) argues that 'knowledge is, unlike information, a flow of messages, derived from either the flow of information or the ways (perceptional, context-specific and purposeful) by which the information is organized or structured.' In addition to such perspectives, there is a plethora of definitions and taxonomies. Nonaka also argues that 'tacit' knowledge is perceivable, but owing to its unstructured nature is difficult to pinpoint, model, or transfer because of the essence of its unstructured nature being experience-based, intuitive, simultaneous, and analog. In addition, 'explicit' knowledge differs from tacit (or implicit) knowledge, because it embodies structural characteristics that enable people to manipulate, organize, model and transfer its essences (such as logical, sequential, and digital attributes).

Anderson (1983) defines 'declarative' and 'procedural' knowledge, based on the structure of knowledge. He adds that declarative knowledge is expressed with a definition implying 'Know-what'. Conversely, 'procedural' knowledge could be defined as 'Know-how' by which manipulation of knowledge itself, or behavioral procedure, is knowledge itself. Consequently taxonomy of knowledge can be dependent upon the ontological and epistemological stance one might take.

Based on previous research, we propose a knowledge taxonomy as in Fig. 1, which consists three types of knowledge: 'Know-what', 'Know-how', and 'Know-why'. Compared to the information aspect of 'Know-what' and procedural aspect of 'Know-how', 'Know-why' is

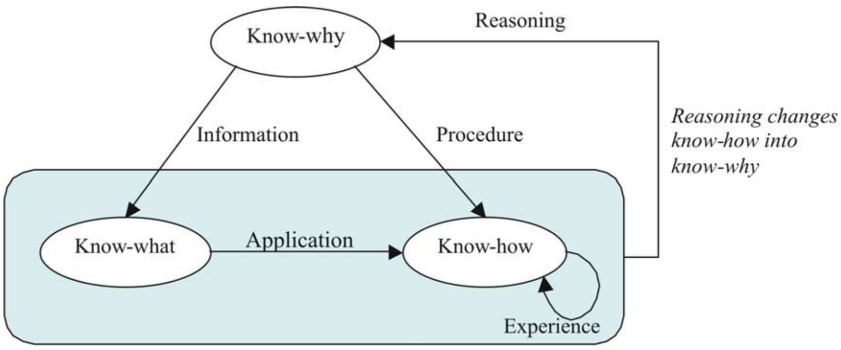

Fig. 1. Conceptualising knowledge.

characterized by the capability of reasoning. 'Know-what' can be applied to 'Know-how', which can be refined by experience. Such experiences enable reasoning as to whether there are better possibilities. The reasoning capability in turn identifies any requirements to modify existing 'Know-what' or 'Know-how'.

2.2. Knowledge management

KM is the process of capturing the collective expertise and intelligence inside and outside an organization and using it to foster innovation through organizational learning (Davenport, Javenpaa, & Beers, 1996; Earl & Scott, 1999; Nonaka, 1991). KM is defined as 'the systematic process of finding, selecting, organizing, distilling, and presenting information in a way that improves an employee's comprehension in a specific area of interest' (KM Center, 2003). While this definition focuses on acquiring knowledge and its management, it aims at utilizing knowledge for various business issues such as problem solving, learning, decision-making, and strategic planning.

The current methods of KM can be classified by knowledge transfer modes (Fig. 2) either tacit/explicit or explicit/tacit mode based on Nonaka's (1994) argument. 'Socialization' is the transferring mode of tacit knowledge to tacit knowledge which examples include British Petroleum's virtual teamwork, tea times and various meetings in corporations; other examples include Hewlett Packard's sales partner system based on Web technology, and benchmarking, etc (Davenport, 1998). 'Externalization' or transferring tacit knowledge to explicit knowledge has been suggested to deploy as a result of document management systems (OpenDocs) or database systems (Andersen Consulting's Knowledge Xchange). 'Internalization' is the transferring mode of explicit knowledge to tacit knowledge, suggested by Nonaka (1994) as a type of organizational learning. In the context of the explicit to explicit mode of 'Combination', it has been suggested to facilitate document management systems, database systems, and expert systems such as data mining or neural networks. Rather than managing knowledge, knowledge mapping has been used for managing the position of knowledge (Davenport, 1998).

Much of the current KM methods focus on the attainment and management of knowledge (Kim et al., 2003; Liebowitz, 2003) and its application to an operational level (Alera, Borrajoa, Camachoa, & Sierra, 2002; Ozbayrak & Bell, 2003); and it is difficult to identify cases of methods that have been applied to help decision-making or problem-solving processes by senior executive management (Alavi & Leidner, 2001; Bennett, 1998; Courtney, 2001; Meso, Troutt, & Rudnicka, 2002). This situation is illustrated in Table 2, where an organization has three layers of hierarchy—top management, middle management, and operation level—and its corresponding characteristics. As indicated in Table 2, knowledge used by top management is related to decision making or strategic planning, in which tacit knowledge outweighs explicit knowledge (Bennett, 1998; Edwards, Duan, & Robins, 2000) and its scope covers most organization. In terms of organizational effectiveness, the hierarchy of knowledge would be much more pervasive than those of two other hierarchies. While middle management needs knowledge related to the operation of a departmental unit (Davenport, 1998; Meso et al., 2002), the hierarchy requires both tacit and explicit knowledge in almost equal proportions. Likewise, the area of knowledge can be limited to a department unit or division level. In conducting individual tasks at the operation level, the proportion of use of explicit knowledge is greater than that of tacit knowledge (Cheng, Luckett, & Schulz, 2003; Edwards et al., 2000).

Many recent methods of KM attempt to measure the level of effectiveness of the individual worker or middle management, as depicted in Table 1. Furthermore, KM methods applied to senior management have been extremely limited by the nature of tasks and areas of their application. In other words, owing to the nature of problems dealt by top management, which can be unstructured, irregular and organizational-wide, it is often difficult to identify the knowledge for solving these types of problem (Bennett, 1998; Edwards et al., 2000). Hitt and Tyler (1991) suggest that executives' experiences may combine in a very complex and even unique way as cognitive models are developed for the purposes of making strategic decisions. Although we assume that identifying knowledge is feasible, it is a non-trivial undertaking to obtain all necessary knowledge due to lack of information or data in a genuine situation. Additionally, although one might possess similar knowledge through previous experiences, it would be difficult to validate that previous knowledge would be effective against new situations and problems (Schmitt, 1997). Knowledge never exists independent of relationships with an event, an idea, or another person. Knowledge is created in relationships, inside thinking, reflecting human beings (Wheatley, 2001) Finally, since a great portion of knowledge required at top management level is contained in decision-makers' mental models, the management of knowledge becomes yet a further complex matter.

		Destination	
		Tacit	Explicit
Source	Tacit	Socialization (Virtual Team Work)	Externalization (Doc. Mgt. System)
	Explicit	Internalization (Organization Learning)	Combination (Doc. Mgt. System, Data Mining)

Fig. 2. Knowledge transfer mode.

2.3. Knowledge based decision making

The study of decision making has evolved in the area of classical decision making (Savage, 1954), behavioural

Table 1
Characteristics of KM in organization

	Top management	Middle management	Individual worker
Applications of knowledge	Decision making, strategic planning	Departmental or divisional task, decision making	Individual task
Types of knowledge	Explicit knowledge ≤tacit knowledge	Explicit knowledge ≅ tacit knowledge	Explicit knowledge ≥ tacit knowledge
Areas of knowledge	Overall organisation	Department or division	Individual task
Significance of organisational performance	Maximum	Medium	Minimum
Knowledge method	Meeting	Benchmarking	Education and training Database, expert system, meeting, community of practice

decision research (Edwards, 1961; Kahneman, Slovic, & Tversky, 1982), judgment and decision making (Meehl, 1954), organizational decision making (March & Simon, 1958; March & Shapira, 1982, 1987), and, more recently, naturalist decision making (NDM) (Klein, 1999; Zsambok, 1997). We can find that these researchers' decision environments have shifted from static and laboratory decision environments to dynamic and commercial business world ones. Additionally, the application of methods will be different depending on the decision-making context: whether it is strategic or operational. From the perspective of decision environments and decision-making targets, we have developed a matrix for applying various methods in differing decision environments, as shown Fig. 3.

In static and laboratory decision environments, principally the stage model (Lipshitz & Bar-Ilan, 1996), AI approach (Mockler, 1989; Mockler & Dologite, 1992; Newell & Simon, 1972), decision tree, and cognitive mapping (Axelrod, 1976) are used for conventional decision-making. Knowledge-based expert systems (ES)

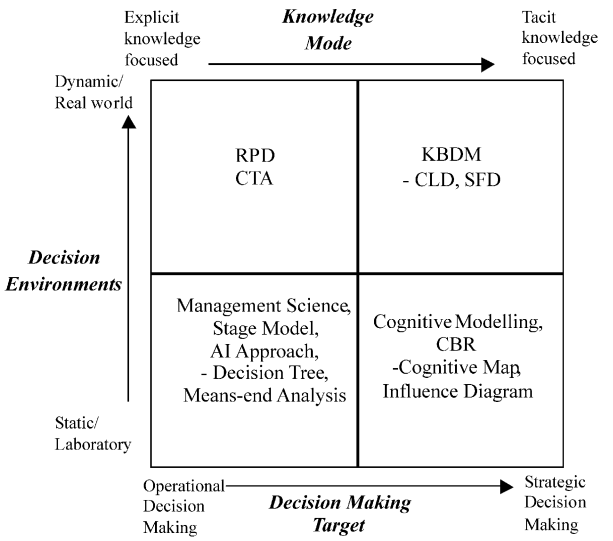

Fig. 3. Applying method in decision environments.

in a replacement role prove to be effective for operational and tactical decisions, but have limitations at the strategic level (Edwards et al., 2000). ES in a support role, as advisory systems, can help to make better decisions, but their effectiveness can only be fulfilled through their users. The AI approach is focused on well-defined problems, but its limitation is a closed problem space generated from a finite set of objects, relations, and properties. Although knowledge-based expert systems have been developed for strategic planning, most ES have not modeled the structure of strategic problems. They have just defined the structure of expert knowledge by integrating with conventional computer systems—especially database and spreadsheet-based system, and financial analyses, modeling, forecasting and reporting system (Liebowitz, 1997; Mockler & Dologite, 1992).

In cognitive modelling, the cognitive map has been a widely used technique. This method has varying nomenclature: cognitive map (Axelrod, 1976; Klein & Cooper, 1982; Tolman, 1948); cause map (Eden, Ackerman, & Cropper, 1992; Hall, 1984); influence diagram (Diffenbach, 1982; Ramaprasad & Poon, 1985); and, knowledge map (Howard, 1989). The cognitive map represents relationships that are perceived to exist among attributes and/or concepts of a given environment. While this model does not consider the time factor, causal concepts may affect each other over time. Therefore, cognitive mapping has a limitation in explaining the dynamic features of the lived world.

Within the context of NDM, for dynamic and lived commercial world decision environments, the most common methods are cognitive task analysis (CTA) (Gordon & Gill, 1997; Klein, Calerwood, & MacGregor, 1989), recognition-primed decision (RPD) model (Janis & Mann, 1977; Klein, 1993), and situation awareness (SA) (Klein, 1999). NDM researchers seek to understand 'cognition in the wild' (Hutchins, 1995) but, arguably, usually focus on the expertise and operational level, not on the strategic decision-making. Expertise is not easily defined in many organizational settings because the outcome of most decisions has multiple causes and effects, most of which any given decision maker is not likely to know or understand. NDM cannot identify the cause-effect relationships and feedback of knowledge and influences of time. The challenges of NDM are to develop simulation methods and to enhance methods of knowledge elicitation (Hoffman, Crandell, & Shadbolt, 1998) of decision-making in naturalistic settings.

RPD explains how people can use experience to make difficult decisions, and demonstrates that people can make effective decisions without using a rational choice strategy (Klein, 1999). Experts use their experience to form mental simulations of the problem currently being encountered and use these simulations to suggest appropriate solutions (Beach, Chi, Klein, Smith, & Vicente, 1997). It is similar to the strategy of case-based reasoning from the theory of expert systems. But RPD does not consider teams, organizations, and issues of managing workload. Also, it does not describe the strategies people use when they do have to compare options in natural settings (Klein, 1999).

CTA describes the expertise needed to perform complex tasks. The steps of CTA are to: (1) identify sources of expertise, (2) evaluate the quality of the knowledge, (3) extract knowledge to get inside the head of the skilled decision maker, (4) codify knowledge, and (5) apply the knowledge (Klein, 1999). CTA can analyze complex, ill-structured tasks, and real time environments. But, CTA can be labor intensive and requires well-trained interviewers to facilitate knowledge elicitation. Moreover, it may not always be possible to conduct such work when needed. Additionally, CTA cannot identify knowledge of where to go in an organization to obtain the relevant information and resources that are required to develop an appropriate decision strategy.

In terms of characteristics of top management decision-making, the decision environments are dynamic and *real world*, and they mainly manage strategic decision-making, and are tacit knowledge focused (Bennett, 1998; Edwards et al., 2000). And, in order to make decisions in the real world, top managers have to manage and use knowledge that is related to strategic concerns. Therefore, we suggest a KBDM method for these situations that will support decision-making or strategic planning by top management levels using the SD as stated in the following section.

3. System dynamics

In this study, we use the systems dynamics (SD) methodology that aims to achieve a realistic and reflective system from a greater understanding of the target system. This is achieved using feedback loops among the system components and identifying the behavior pattern over time. SD consists of four components: system, feedback, level, and rate.

3.1. System

Although there is a plethora of system definitions, there is a common view that a system tends to incorporate a set of elements sharing a particular purpose within a boundary Depending on its boundary, a system can be a corporation, an environment, an economic entity, a country, an inventory system, etc. The system should have ‘emergent properties’ (Checkland, 1981) or ‘synergy’ out of interactions and relationships amongst elements. However, the emergent properties are dynamically changing with time. Consequently, to examine the system it is necessary to specify its ‘closed boundary’, to confine the scope of interaction within a time frame and within a particular problematic area. The closed boundary should embrace all target systems, and it should prevent internal elements being influenced from external environments. The interaction of elements inside the closed boundary determines a structure of the system. Similarly, to conceptualize a system it is necessary that the elements of system and their interaction should be analyzed and modelled. For modelling causal aspects of interaction in a system, Section 3.2 will introduce the concept of feedback.

3.2. Causality and feedback

The casual relationship indicates one element affecting another element In order to model the causality, a causal-loop diagram (CLD) has been used. CLD has been used to formulate a cognitive model and to hypothesize the dynamic interactions between elements. Representing the feedback of related elements requires additional positive (+) and negative (−) polarity to the CLD diagram. A positive relationship is presented with ‘ + ’ and a negative relationship with ‘ − ’ as in Fig. 4. Positive relationship refers to ‘a condition in which a casual element, A, results in a positive influence on B, where the increase of A value responds to the B value with a positive increase.’ (Richardson, 1986) Negative relationship refers to ‘a condition in which a causal element, A, results in a negative influence on B, where the increase of A value responds to the B value with a decrease’. (Richardson, 1986)

The dynamic movement of the system can be caused by a feedback loop, and there are two types of feedback: reinforcing (R) and balancing (B). As illustrated in Fig. 4, increases in population increases the numbers of birth, which again increases the overall population: ‘reinforcing

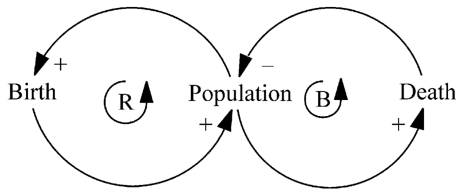

Fig. 4. The diagram of casual relationship.

loop'. To the contrary, the greater the population, the higher the number of deaths, and then the population decrease: 'balancing loop'. Likewise, it is not easy to understand the complexity involved with the dynamic changes among elements and the target system in which casual relationships and feedback loops exist.

3.3. Level and rate

Whilst the simplicity of CLD has improved communication and comprehensiveness among its users, it does not reflect all elements for sensitivity testing a target system There are two variables required for simulating all elements inside a system: level and rate. The 'level' refers to a given element within a specific time interval. For example, a company should have 2002's total turnover and inventory level on December 2002, or current total employee number, and so on. Meanwhile, the rate reflects the extent of behavior of a system, such as hourly production volume, and daily sales turnover. Specifically, the differences between the level and the rate depend on whether the element contains a time factor.

The level is calculated from the difference between a rate variable that increases the level and a rate variable that reduces the level. In short, the level has only something to do with rates related to input and output; other rates are irrelevant. A value of level (an accumulated rate) can be identified easily, but a rate is not easy to be identified. In most cases, a rate is calculated by averaging the accumulated levels over the total time taken. For instance, it would be difficult to find out the hourly order rate from customers at present, but it can be calculated by dividing the accumulated order number using working hours. The level and the rate can be formulated using the stock-flow diagram (SFD) for a simulation test. The level can be represented with a stock level; the rate is described as a variable on the flow. The value of stock at t time would be made by adding the initial stock value ($\mathrm{Stock}_{t-\mathrm{d}t}$) to the input and output difference during the time, dt. Stockflow formulas are depicted as follows:

$$\mathrm{Stock}_t = \mathrm{Stock}_{t-\mathrm{d}t} + \mathrm{d}t(\mathrm{Inflow}_{t-\mathrm{d}t} - \mathrm{Outflow}_{t-\mathrm{d}t}) \quad (1)$$

or

$$\mathrm{d(Stock)/d}t = \mathrm{Inflow}_t - \mathrm{Outflow}_t \quad (2)$$

CLD in Fig. 4 can be modelled as a SFD in Fig. 5. 'Stock' is represented as a rectangle, 'Flow' can be expressed as a double-direction arrow. In the example shown in Fig. 4, the variable entitled 'population', is only depicted as the stock (unit: person), whilst both 'birth' and 'death' (unit: person/year) are presented as the flow. As shown in the Fig. 5, additional variables for the simulation are also added to SFD. Fractional birth rate describes birth rate per person. For instance, a couple has two children throughout their

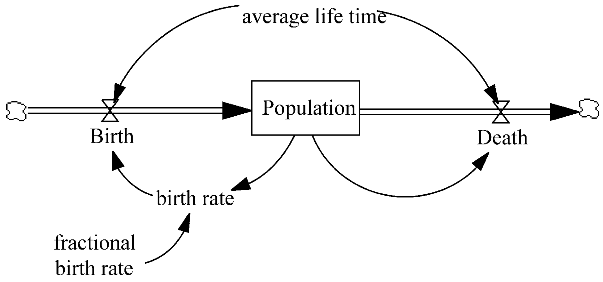

Fig. 5. Stock-flow Diagram.

lifetime and the fractional birth rate can be 1 (unit: dimensionless). If the current number of population is one thousand, the expected numbers of birth on the current population will be one thousand (birth rate = fractional birth rate × population). Meantime, this birth is a long run process throughout one's lifetime, one that belongs to the population stock. Subsequently, yearly birth rate, 'Birth', can be obtained by birth rate/average lifetime. The age distribution of population stock is assumed as a uniform distribution, and the male to female ratio is assumed as one to one. Similarly, yearly death rate, 'Death', can be expressed by an equation, population/average lifetime (expectancy). As depicted in the Fig. 5, the birth increases the population, and it also proportionally increases the death. This will lead to the decrease in population, which in turn, decreases birth. Consequently, a non-liner relationship exists among variables, and then the population cannot be calculated through linear equations.

4. System dynamics approach for knowledge based decision making

4.1. Assumptions of the method

KBDM method enables managers to make decisions under dynamic non-trivial environments with system dynamics. To address the issues identified in the previous section, our method is based on the following underpinning assumptions.

Decision-making and knowledge are closely linked. When individuals or groups make decisions without full consideration of organizational parameters, the decisions made may be sub-optimal from the organizational perspectives. Hall, Paradice, and Courtney (2001) argue that DSS is on the verge of a paradigm shift. This shift is needed to adequately support organizational learning (Stein, 1995) and KM and organization learning and KM are activities executed to take organizations toward desired goal. Liebowitz and Beckman (1998) observe that KM must be integrated within the strategic goals of the organization in order to fully realize its potential for enhancing organization performance. And, in a model for problem solving (Pylyshyn, 1984; Smith, 1989), argue that it is important to represent the problem in an explicit manner. These are decision making; with knowledge and organization learning linked closely.

Top management make decisions approximating NDM. Bass (1983) suggested that strategic decision-making is a messy rather than orderly process. Most upper level decision makers are routinely required to make sense of a wide variety of unstructured, complex, and often conflicting information (Edwards et al., 2000; Sternberg, 1997) in dynamic, uncertain, highly constrained timeframes, and real time environments. And decisions evolve through a complex, non-linear, and fragment process (Bennett, 1998). Strategic decisions often have no precedent or guide and are often not easily modelled or analyzed (Daft & Lengel, 1986; Dean & Sharfman, 1993).

Focus on application of knowledge in decision making, rather than decision making method

As reviewed in Section 2.3, a decision-making method is generally defined. And application of knowledge in organization and decision-making (Alavi & Leidner, 2001; Courtney, 2001; Hall et al., 2001; Ozbayrak & Bell, 2003) is an extensive research issue, and highly relevant in the field.

Adopt SD techniques and concepts in order to apply in dynamic and real-world environments. (Kim & Senge, 1994)

System dynamics is the most appropriate approach to dynamic environments. SD's development was based on systems thinking (Forrester, 1961; Senge, 1990), the ability to see the world as a complex system, in which we understand that 'everything is connected to everything else' (Senge, 1990; Sterman, 1991, 2001). In the dynamic complexity, people find most problematic issues of feedback, time delays, accumulation, and nonlinearity (Sterman, 2001). As reviewed in Section 3, SD can explain well facets of dynamic complexity and real world attributes.

4.2. Method of knowledge-based decision making

KBDM consist of ifve phases, which are: (1) Define problems, (2) Conceptualization of Knowledge, (3) Formulation of Knowledge Model, (4) Testing and decision making support, (5) Applying. We summarized the phase of KBDM in each phase in Table 2, respectively.

4.2.1. Phase 1. Define problems

The first phase consists of defining problems (strategic issues). The main objectives of this phase are understanding the problems that are to be resolved, and identifying sources of knowledge. Problem solving is the underlying thinking done in anticipation of action (Smith, 1989). One thinks about a problem in order to determine what action to take in pursuit of one's objectives. Cognitive science holds that problem solving, like all mental activity, works from a representation, performance being strongly affected by representational adequacy (Pylyshyn, 1984; Simon, 1978). In order to identify source of knowledge, we find that there is not one expert and, therefore, review related documents. Usually, we find that there are not one people, but rather, different people knowing worthwhile things in different areas.

We represent a problem (strategic issues) as a notation, ⟨'Situation', anticipation, 'goal'⟩, which a given situation and the anticipation that one may wish to fulfil with regards to the situation; and the goal is what to get as a result. For example, we can define ⟨'Marketing activities are very weak', Increase customer adoption and retention by promotion, '10%'⟩

Factors that relate to a situation and allow anticipation, will be major causal elements in CLD. Consequently, the goal is set as stock factors in SFD and is used in the test phase as an alternative.

4.2.2. Phase 2. Conceptualization and integration of knowledge

Based on the problem selection and its definition, it is necessary to extract the knowledge, and determine the relationships between elements and the dynamics' hypotheses. The dynamic hypotheses can be conceptualized by CLD to describe the causal relationships among elements. These methods included focused group interviews, discussions about actual events that were challenging, and interviews about the concept that experts use to think about the issues based on the situation and boundaries defined in phase 1. However, individuals or functional departments have very limited knowledge. Their partial knowledge from different sources therefore needs to be reorganized and combined into an integrated knowledge model for conceptualizing the target management problem.

This phase of our work developed the structure for understanding business concerns using CLD and explicit and implicit representation of a problem. Upon establishing the problem definition, we identified the key variables. Variables are the components of the problem whose value

Table 2
Five phase of KBDM application

Phase	Tasks/activities	Output	Technique
1	Define strategic issues and identify sources of knowledge	Strategic issues, scope, and knowledge	Interview, brainstorming, document analysis
2	Conceptualization and integration of knowledge	CLD, problem statements	Focused group interview
3	Formulation of knowledge model	SFD decision requirements	Focused group interview, feedback analysis
4	Decision making support	Simulation test	Simulation test, focused group interview
5	Applying	Feedback	

can vary up and down over time. This allows results to be expressed in graph form to show variable's behavior over time. In this phase, usually, we ask questions like, 'What's causing these events?' or 'Why is this pattern happening?' or 'What structures are in place that are causing these patterns?' We are thinking in terms of casual connections and probing at structure. Then we can identify problems' causes by causal reasoning.

4.2.3. Phase 3. Formulation of the knowledge model

In the formulation phase, the CLD is extended to Phase 2 allowing a testable SFD. For the formulation, there is a need to find additional quantitative variables to support mathematical formulation. Next, there is a requirement to assign values to the formulated model. For this purpose, there is a need to gather basic data from company report (i.e. constant, rate) for simulation, developing a database, allowing statistical manipulation of data. Of noteworthy significance, the integrated knowledge models developed in phase 2, are elaborate in this stage. Next, the formulated model needs verification and validation to ensure the formulated model represents the conceptual model, CLD, and whether it shows the same historical behaviour pattern of the real world situation. For this validation, various methods (Peterson & Eberlein, 1994; Sterman, 1991) can be applied as verification of feedback loops by decision makers, comparison of historical data to simulation output, validation on the model in extreme circumstances, and sensitivity tests on various variables.

4.2.4. Phase 4. Decision making support

In the decision support phase, diverse alternatives need to be tested for decision-making based on the validated model. Consideration should be given to whether the decision alternatives have taken into account all circumstances. It tests over time which alternative is the most effective and also whether the alternative shows effective results. By considering the dynamic changes over time, planning of decision-making, and multiple decisions making over time can be considered. This process leads to the final stage of suggesting a decision-making alternative.

4.2.5. Phase 5. Applying

It suggests a decision making alternative, as well as capturing tacit knowledge and making it accessible for training and information system design. It can also be applied as an organizational memory.

The order of applying these phases can be changed, dependent upon the complexity of the targeted problems and data availability. For example, like an inventory system, where the boundary of the system is rather small and all the necessary data can be obtained, all four phases can be applied and can be capable of reaching optimum decision-making. Nevertheless, for such cases as the national economic system or a company system, where boundaries are too large to obtain all information needed for simulation, only phase two or phase three can be progressed to describe the feedback structure on the system and the dynamic pattern change.

5. Comparison of system dynamics with other methods

As a research method, the SD approach can be compared to Management Science. However, the research on SD starts with a different assumption from the traditional assumptions of Management Science. (1) Developing models based on numerical figures, (2) analyzing most problems by linear relationship, (3) reflecting a limited number of variables which are influenced by results in a static condition, (4) accuracy of model parameters is more important than the overall problem structure, and (5) pursuing optimal support decision making. (Richardson, 1983).

With respect to the first assumption of numerical data, the number of this type of data is extremely limited in comparison to that of all recognizable variables in real systems. Furthermore, providing that real systems are modelled by data expressed with numerical data, this certainly leads to restriction on applicability. Soft variables like customer satisfaction or marketing promotion act to take a very important role in the process of real world decision-making. In the analysis of linear relationships, complexity—such as complex feedbacks—caused by interactions among elements in the system cannot be modelled with linear relationships. In case of the third assumption on the static nature of data, various feedbacks dynamically influence the overall system through the flow of time. Consequently, relationships of dynamic feedback and all relevant variables should be recognized. (Manzoni & Angehrn, 1998) The accuracy of parameters, optimal value obtained from the system—where feedback is not reflected but, still containing accurate parameter values—cannot be regarded as a correct value since not all feedbacks are included in calculating the optimum value. Lastly, the assumptions on the pursuit of optimum, the complexity of the system, accessibility of necessary data and accuracy of data are those that determine feasibility of obtaining optimum.

6. Application case

We applied the proposed KBDM as a knowledge-based decision making method to a US-based local telecommunications company: BmT. BmT was established in 1998 and since the beginning of 1999, it has provided a local telephone service. The major concern for BmT was to increase revenue by capturing market share. BmT adopted a multi-level marketing strategy and focused on finding a niche market based on the demographic segmentation—it targeted on newly developed and highly populated areas like apartment blocks, instead of undifferentiated individual households. In this application case, we aim to understand the target business system and its behaviour mechanism by organising partial and tacit knowledge for decision support. We used VenSim (http://www.vensim.com) software for knowledge modelling, formulating, and final testing.

6.1. Conceptualization and integration of knowledge

The knowledge related to the objective is dispersed across BmT and kept by top management, department managers, and customers. We needed to identify and organize the knowledge from the revenue-oriented perspective—'Externalization' and 'Combination'. In order to identify knowledge related data to support the objective, it was necessary to identify the primary sources. This type of knowledge often exists as cognitive models of top management, department, individual employee, or even customers, represented as documents or databases. Interviews were used to identify the knowledge from top managers, departmental middle managers and those with types of knowledge depicted in the CLD diagram; and simplified in Fig. 6. As shown in Fig. 6, four enforcement feedback loops include: customer adoption, sales efforts, customer service, and claim settlement, along with two balance feedback loops: competition and obsolescence.

As a reinforcing loop, the 'customer adoption loop' shows how the existing customers' Word-of-Mouth (WOM) has taken effect on capturing new customers. The more the number of BmT customers, the higher the WOM effect. That is, current BmT customers would contact other possible customers, leading more customers to adopt the BmT telephone service. The 'Sales effort' loop represents the relationship of how increasing the promotion budget obtained from increasing the customer base (market share) has influenced the capturing new customers. The 'Service efforts' loop represents the relationship of how an increased customer service budget decreases the settlement delay and, in turn, increasing the degree of BmT's attractiveness. 'Claim settlement' loop is related to the relationship of what extent the speedy settlement of customer claims can improve its attractiveness.

As a balance loop, the 'Competition loop' implies that BmT's increasing revenue increases competitors' awareness, reinforcing the sale operation or the emergence of new competitors in the market. This whole process results in alleviating the attractiveness of BmT. 'Obsolescence loop' supports the notion that the increase of BmT customer proportionally increases the number of unsatisfied customers and the delaying settlement. It will decrease attractiveness of BmT and customers will move to other competitors.

6.2. Formulation of knowledge model

Whilst the CLD shown in Fig. 6 is constructed for understanding the target structure and by deriving partial knowledge from the knowledge-holders' mental models, the formulation model is principally for simulation exploration and validating decision alternatives. The CLD of BmT is transformed into a formulation model, resulting in a simplified model as shown in Fig. 7. Customers are classified as potential customers, BmT's regular customers, or loyal customers Multi Level Marketers (MLMers). BmT's customers are a sum of ordinary customers plus MLMers. Changing potential customers to BmT's regular customers can be possible through either 'adoption from sales effort' or 'adoption from word of mouth'. A part of BmT's regular customers can become MLMers by contracts

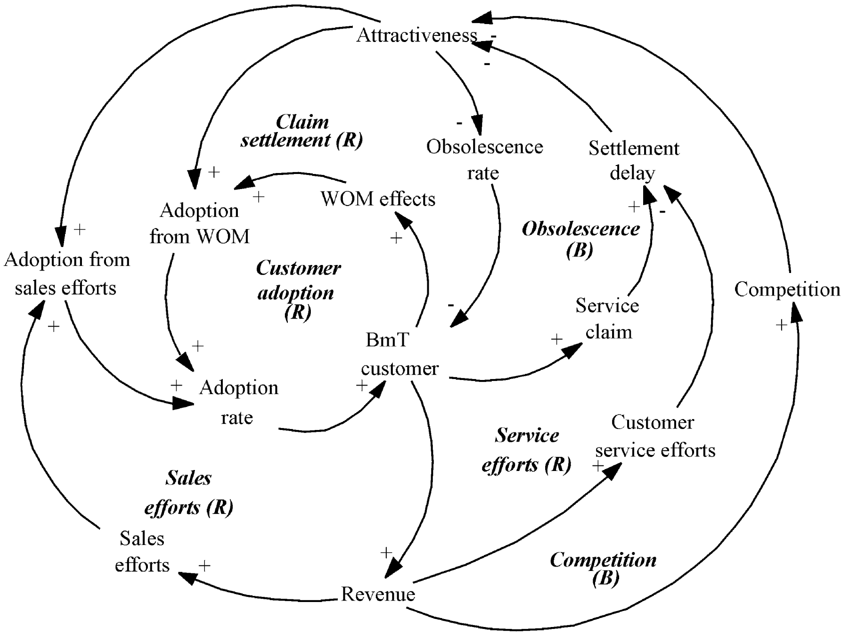

Fig. 6. Revenue-oriented CLD of BmT.

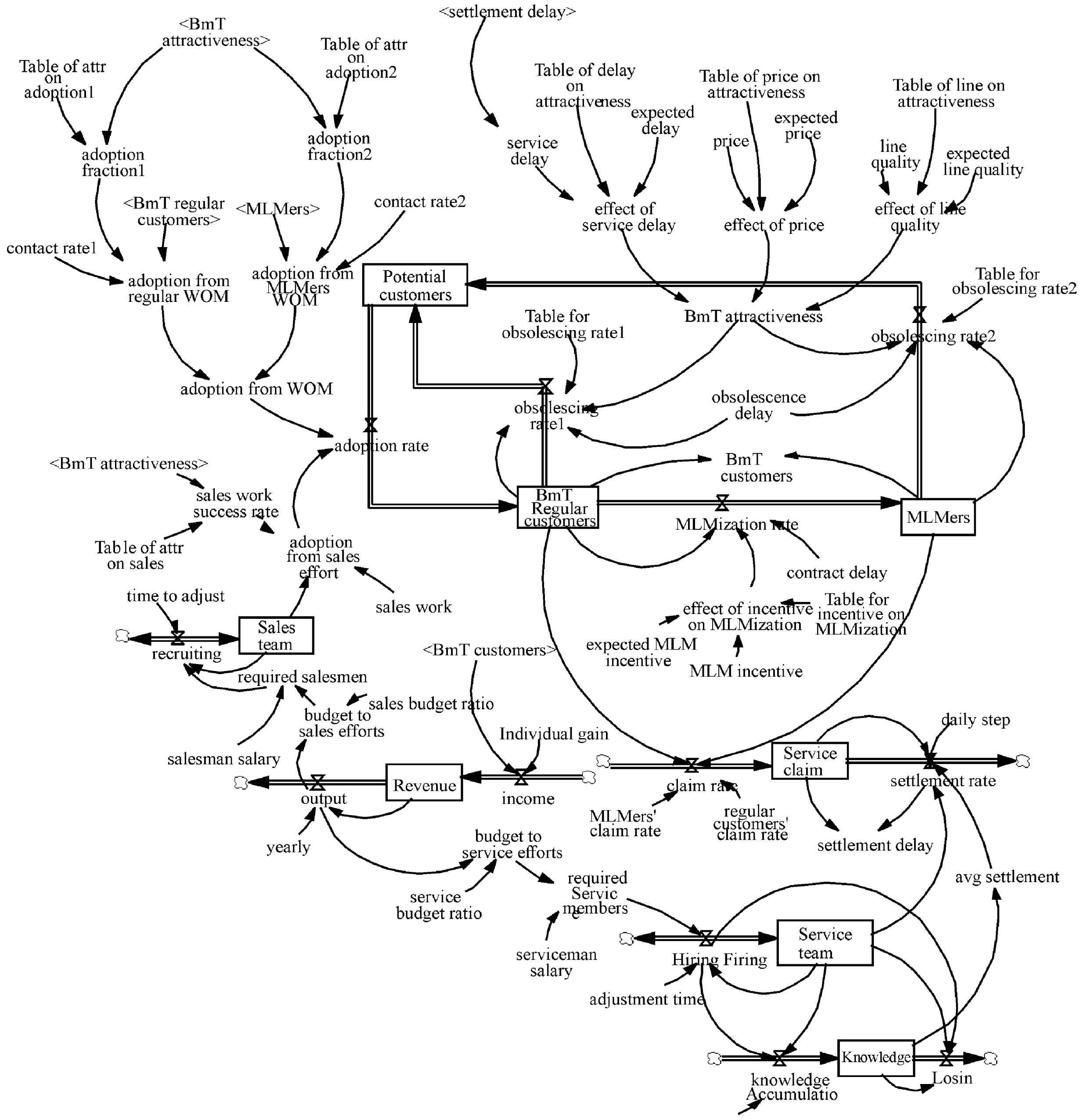

Fig. 7. Revenue-oriented SFD of BmT.

and incentives for capturing new customers, thus playing an important role in this process. The total number of BmT customers determines the revenue; in turn, becoming a base for reallocating budget to the sales team and the customer service team. With the allocated budget, new sales members are hired and sales activities on the potential customers are undertaken. The customer service team aims to install new lines and handle customer complaints. Here the settlement delay time regarding customer complaints impacts BmT's attractiveness. The complaint clearance ratio, by accumulating experience, would eventually improve productivity.

The attractiveness of BmT consists of 'service delay effect', 'price effect', and 'line quality effect' where these values can be calculated by discrepancies between actual values and expected values. Service delay time can be updated automatically by the settlement delay time. The expected price of customers is affected by the competition between local telephone service providers while the price is BmT's actual service price. Although 'line quality' is a soft variable, we quantified it using customers' perception. Similar to the 'expected price', 'expected line quality' is affected by competition. The three table functions – 'Table of delay on attractiveness', 'Table of price on attractiveness', 'Table of line on attractiveness'—determines the impact of each factor on the attractiveness. The higher the attractiveness, the higher the adoption rate and the lower the obsolescing rate. In addition, the attractiveness affects the 'sales work success rate'. Fig. 7 shows the formulated model and its equations are illustrated in the Appendix A.

6.3. Testing and decision making support

In addition to the model verification by BmT management, the model was partly validated by comparing the historical data on new customers for the past 7 months (whilst also having checked the validity in extreme cases). The formulated model ran for approximately 4 years. Based on the current strategy—we lowered the price on the existing service provider by ten percent and adopted MLMers. No new competition was assumed. Fig. 8, depicts the expected outcome of performance. At the commencement of simulation, due to the number of customers being small, their complaints could be incorporated within a short time. However, when the number of customers increased after six months, the number of complaints accelerated with a consequential increase in model running time. This resulted in lowering the attractiveness of BmT, along with the slowing down rate of adopting new BmT customers. Nevertheless, the number of customers was steadily increasing, as was the revenue of BmT. Besides the price, the service settlement delay was then a little shorter than competitors and the line quality was almost equal that of its competitors.

Meanwhile, the low price strategy resulted in increased attractiveness. In attracting new customers, the existing customers' WOM resulted in being more successful than sales activities in the sales department. In particular, the sales operation by MLM customers, that were 5% of total customers, was estimated to capture approximately 50% of new customers. Considering their contribution, a key role by MLM customers is further anticipated through a MLM incentive scheme. In addition to sales teams in new cities, new regions, or a newly developing residential area should remain to seize new markets.

Introducing a low price strategy by BmT was expected to induce the same low price strategy by its competitor. In order to test the customer behavior by this strategy, a scenario of

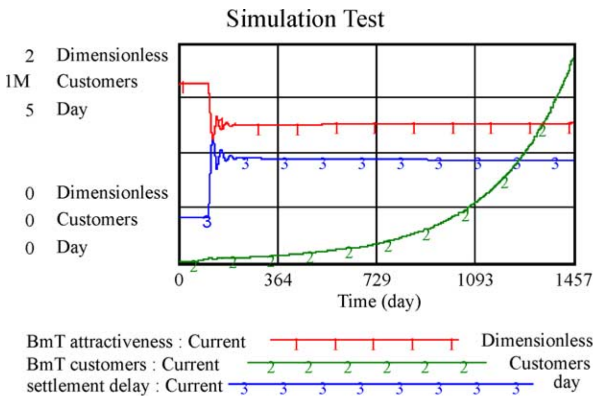

Fig. 8. Simulation result of BmT's current strategy with no competition.

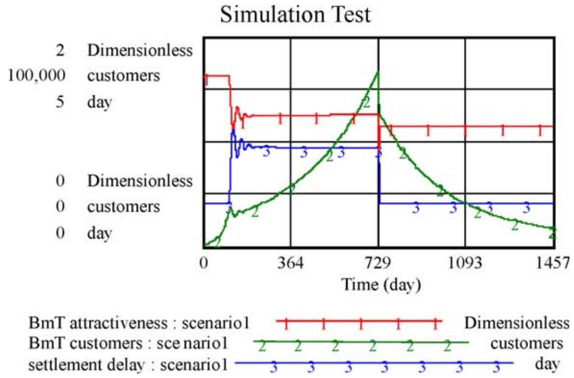

Fig. 9. Scenario test on competitor's price reduction.

a lower price strategy by the competitor—5% lower than that of BmT—was introduced for 730 days (around 2 years), at the commencement of the BmT simulation. As shown in Fig. 9, BmT's attractiveness has degraded by the effects of competition on day 730. Decreased attractiveness resulted in difficulty of capturing new customers, and retaining existing customers. This resulted in the number of BmT customers sequentially decreasing. Conversely, decreasing the number of customers reduced the number of complaints, that in turn shortened the service delay and prevented attractiveness to decline.

In case of a competitor's low price strategy resulting in problems for new market share, BmT was able to deploy various available options for a counter strategy: such as an increase in the sales budget, an increase of the service budget, thus reinforcing MLM incentive, cutting-down on service delay time, lowering service price, and improving the line quality. In choosing various alternative options for the counter strategy, the basic direction on decision-making should be related to improving the attractiveness and reinforcing sales activities. As a counter strategy against the competitor's low price strategy, we could introduce further a price-cutting strategy, which will eventually improve BmT's attractiveness. However, testing of this scenario was excluded from the simulation in order to achieve, at least, 'zero sum game' rather than 'all lose game' situation by the fierce price war.

In reinforcing the sales operation, a MLM incentive can be considered to be a key factor in capturing new market share. For simulating the hypothetical scenario, MLM incentives were increased up to twenty percent. As a result, shown in Fig. 9, BmT customers have increased continuously. However, the increase of new customers also increases the number of complaints that eventually reduced the attractiveness through service delay. Consequently, new decision-making should be made to reduce the average service settlement delay. To undertake this plan, additional budget should be allocated to service efforts based on the amount of claims. With this decision of further allocating budget, BmT is expected to tackle the price competition shown in Fig. 10. Customers tend to be price-sensitive, and are also sensitive to service delay. From this, we can

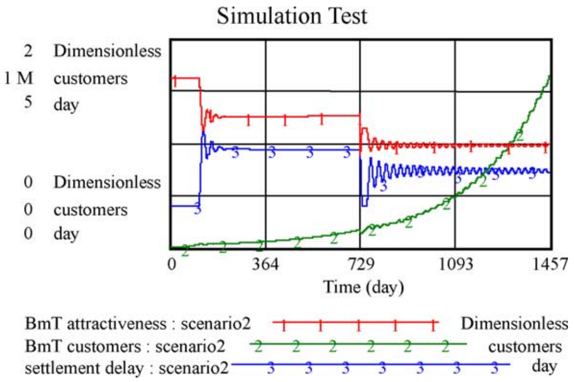

Fig. 10. Simulation test on BmT's reaction scenario.

understand that keeping BmT customers and enhancing MLMers' efforts are a prerequisite for increasing market share since existing customer groups are a source of WOM that affects new customer adoption.

7. Comparison of KBDM with other models and frameworks

The proposed method in this research can be compared to other KM approaches applied to various decision making environments, as in Table 3. We categorized the models and frameworks into case-based reasoning (CBR), knowledge-based systems (KBS), and KBDM according to the application, type of knowledge and the basis of decision making. While CBR uses cases and KBS uses predefined expert knowledge, KBDM uses dynamically integrated models as the knowledge base.

KBS belong to one domain of Artificial Intelligence research. KBS operate at the three levels: assistant, colleague, and expert (Mockler, 1989). KBS are designed to replicate the functions performed by a human expert in a specific decision domain or situation. KBS have been promoted as safeguards to ensure the retention of expert knowledge, and to avoid knowledge erosion (Hendriks & Vriens, 1999). O'Leary and Turban (1987) pointed out that since ES are designed for tasks in narrow domains, the greatest use of ES would occur in operational control decisions. ES would be used least readily in strategic planning because many tasks in strategic planning involve broad domains and many variables. Other research (Edwards et al., 2000) supports this viewpoint. The small proportion of ES used for strategic level decisions may suggest that ES are not good at the strategic level or their potential has yet to be realized (Wong & Monaco, 1995) or that they are rarely employed for strategic planning in business strategy (Mockler & Dologite, 1992).

Most of senior managers are faced with complex and dynamic decision environments, but with the exception of KBDM most frameworks treat decision contexts as static. In relation to the decision making target, the KBDM model suggested in this research has been applied principally to top and middle management, while CBR, KBS, and most other KM approaches have focused on individual personnel for operational purposes. From the perspective of knowledge elicitation, KBDM generates an integrated and dynamic knowledge model from the tacit knowledge across various functional areas; other models tend to assume that the knowledge used in decision making is fixed. Such models highlight both declarative and procedural knowledge, which is related to an individual employee's cognitive models and stored as documents or database types respectively. However, the proposed method in this research emphasizes that declarative knowledge can be derived from causal relationships that reside in cognitive models. This approach can be used flexibly to become a basis of formulating business decision-making or strategic planning.

As an advantage of KBDM in identifying knowledge, we can identify partial knowledge from the cognitive models of decision-makers, middle managers, and customers, and transform them into an explicit integrated model: that is, the externalization and combination of knowledge identified by Nonaka (1994). These models make it possible to impose structure on an ill-structured problem, which enables us to understand the structure of the target problem. In addition, decision-makers can learn the behavior mechanism of the target system by understanding and testing the knowledge model: these processes are described as socialization and internalization by Nonaka (1994). This implies that KBDM can be applied in the area of organizational learning. Learning allows individuals to obtain knowledge and insight from the results of past experiences, and apply these to future circumstances (Fiol & Lyles, 1985).

Table 3
Comparison of KBDM with other frameworks

	CBR	KBS (expert systems)	KBDM
Decision environment	Static	Static	Dynamic
Decision making target	Operational	Mainly operational	Strategic issues and problems
Knowledge model	Explicit knowledge	Expertise and revealed information	Tacit knowledge
Knowledge transfer	Externalization	Externalization, combination	Externalization, Internalization, combination
Knowledge representation	Concept, relationship	Production rules, predicate logic, frames, neural nets	Concept, relationship, statements (formula)
Knowledge sources	Case	Predefined expert knowledge	Dynamic integrated knowledge model

As a result, KBDM enables us to organize and model knowledge by capturing casual relationships between pairs of elements. Testing strategies over time with the aid of simulation scenarios can be considered as a significant advantage of KBDM. The proposed KBDM method aims to design better-behaved systems by structuring problems with feedback loops, while introducing and allowing for non-linearity and dynamic time perspectives.

AI and KBS technologies are often based upon the assumptions that human intelligence and experience can and should be stored. The *static* representations of data in databases, inferential logic of computer programs and computer memories lack inherent *dynamic* capabilities which are increasingly relevant for emerging business environments (Malhotra, 2001). In contrast with this feature of KBS, the present study proposes a knowledge-based decision support method which can be applicable in the dynamic business environment. As a practical method, it provides detailed procedures to leverage tacit knowledge in the process of decision making.

8. Discussion and implications

This research can be discussed in the context of knowledge conceptualization presented in the previous sections. During the conceptualization process, the knowledge related to the target problem was identified (Know-What), structured (Know-How) from the causal relationship perspective with the CLD translated mental model of partial and implicit knowledge into an explicit knowledge. During the formulation process, the organized knowledge model was transformed into a simulation-possible model with SFD, by adding additional decision (Know-What) and simulation factors. During the decision make support process, the performance of the formulated knowledge model could be evaluated. Testing of the decision-making support process enabled decision-makers to trace the basic cause of unexpected outcomes, to understand which decision factor has a higher impact on performance, and to discern decision alternatives (Know-Why). Suggested decision alternatives, again, have effects either on the value of decision factors (Know-What) or the causal relationships (Know-How). In particular, organizational change such as business process redesigning requires modifications in the structure of knowledge relationships.

The proposed integrated knowledge model in KBDM is much more useful in understanding the target situation because the effectiveness of integrated knowledge is bigger than the sum of individual effectiveness: effectiveness (knowledge1 + knowledge2) $\geq$ effectiveness (knowledge1) + effectiveness (knowledge2).

There are several implications in this research. Firstly, this research proposed how we can organize knowledge by deriving partial knowledge from the target situation-related personnel's cognitive models. Since most knowledge resides in cognitive models, they are rather tacit and ethereal. The integrated knowledge model is useful in structuring the target business problem. Secondly, the proposed approach supports management in making decision by focusing on the problem structure rather than on behavior patterns or events, (most decision making methods focus on events). The impact in decision-making is increased from the event to the behavior pattern, and again to the problem structure. Thirdly, the proposed approach enables decision-makers to learn the behaviour mechanism of the target business system and to get feedback. The feedback is insufficiently present in organizational systems on account of technological difficulties and interpersonal relationships (Skraba et al., 2003). During the learning process, decision-makers can identify the relative impact of decision alternatives on the target problem over time.

9. Conclusion

As a new asset in reinforcing organizational competitiveness, knowledge management has often been suggested, and its management and application has been widely studied. Despite the fact that it has such a wide acceptance, most KM research has aimed to identify, store, and diffuse knowledge for the accomplishment of tasks more effectively. In comparison, we propose the application of KBDM for knowledge based business decision-making and strategic planning which is at the core of business management. This method facilitates the linkage between KM initiatives and achieving strategic goals and objectives of an organization. Furthermore, this research makes an important contribution by providing a starting point of future research through the combination of knowledge management and system dynamics.

A limitation in the proposed approach is that it is not easy to validate the organized knowledge model because its structure is based on cognitive models. For validating the relationships among the partial knowledge factors, problem-related personnel should join together in verifying the model. Yet another limitation would be a lack of relevant data for testing. In most business situations, information without any specific purpose is rarely kept. Consequently, additional data collection efforts—reviewing and analyzing the existing data and conducting interviews—should be completed. Upon collecting all the required data for testing, there are several ways to validate the formulated knowledge model, such as sensitivity testing and matching between the test results and historical data. The most important aspect in validation, however, is to check the accuracy of the structure of the knowledge model. To overcome these limitations, a more effective validating method should be developed and applied.

Appendix A. Knowledge model formulation (Fig. 7)

experience over time = 180 ~day

knowledge accumulation = Service team/(Hiring Firing + Service team)/experience over time ~Dimensionless

Knowledge = INTEG (knowledge accumulation-losing,1) ~Dimensionless

losing = IF THEN ELSE(Hiring Firing < 0, Knowledge * Hiring Firing/(Service team + Hiring Firing),0) ~Dimensionless/day

avg settlement = 32 + Knowledge ~claim/day/person

yearly = 365 ~day

budget to service efforts = output * service budget ratio ~$/day

obsolescing rate1 = BmT regular customers * Table for obsolescing rate1(BmT attractiveness)/obsolescence delay ~customers/day

obsolescing rate2 = MLMers * Table for obsolescing rate2(BmT attractiveness)/obsolescence delay ~customers/day

output = Revenue/yearly ~$/day

Revenue = INTEG (income-output, 2e + 006) ~$

Hiring Firing = (required service members-Service team)/adjustment time ~person/day

budget to sales efforts = output * sales budget ratio ~$/day

Service team = INTEG (Hiring Firing,10) ~person

income = BmT customers * individual gain ~$/day

adoption from regular WOM = contact rate1 * BmT regular customers * adoption fraction1 ~customers/day

adoption from MLMers WOM = contact rate2 * MLMers * adoption fraction2 ~customer/day

daily step = 1 ~day

settlement rate = IF THEN ELSE(Service claim/daily step > Service team * avg settlement, Service team * avg settlement\, Service claim/daily step) ~claim/day

service delay = settlement delay ~day

time to adjust = 14 ~day

adoption fraction1 = Tabel of attr on adoption1(BmT attractiveness) ~Dimensionless

adoption fraction2 = Table of attr on adoption2(BmT attractiveness) ~Dimensionless

BmT customers = BmT regular customers + MLMers ~customers

serviceman salary = 100 ~$/day/person

adoption from sales effort = sales work success rate * sales work * Sales team ~customers/day

adoption from WOM = adoption from MLMers WOM + adoption from regular WOM ~customers/day

Table of attr on sales(((0,0)-(8,1)),(0,0.01),(1,0.2),(8,1)) ~Dimensionless

required salesmen = budget to sales efforts/salesman salary ~person

required service members = budget to service efforts/serviceman salary ~person

sales budget ratio = 0.15 ~Dimensionless

Table of attr on adoption2(((0,0)-(8,1)),(0,0),(1,0.3),(8,1)) ~Dimensionless

sales work success rate = Table of attr on sales(BmT attractiveness) ~Dimensionless

contact rate1 = 2 ~customer/day/customer

contact rate2 = 10 ~customer/day/customer

individual gain = 0.7 ~$/customer/day

salesman salary = 95 ~$/person/day

Potential customers = INTEG (obsolescing rate1 + obsolescing rate2-adoption rate, 1e + 008) ~customer

Table of attr on adoption1(((0,0)-(8,1)),(0,0),(1,0.01),(8,0.4)) ~Dimensionless

recruiting = (required salesmen-Sales team)/time to adjust ~person/day

service budget ratio = 0.04 ~Dimensionless

Sales team = INTEG (recruiting,15) ~person

sales work = 10 ~customers/person/day

adjustment time = 30 ~day

adoption rate = adoption from sales effort + adoption from WOM ~customers/day

BmT attractiveness = effect of line quality * effect of price * effect of service delay ~Dimensionless

BmT regular customers = INTEG (adoption rate-MLMization rate-obsolescing rate1, 100) ~customers

claim rate = BmT regular customers * regular customers' claim rate + MLMers * MLMers' claim rate ~claim/day

contract delay = 10 ~day

effect of incentive on MLMization = Table for incentive on MLMization(MLM incentive/expected MLM incentive) ~Dimensionless

effect of line quality = Table of line on attractiveness(line quality/expected line quality) ~Dimensionless

effect of price = Table of price on attractiveness(price/expected price) ~Dimensionless

effect of service delay = Table of delay on attractiveness(service delay/expected delay) ~Dimensionless

expected delay = 2 ~day

expected line quality = 1 ~Dimensionless

expected MLM incentive = 1 ~$/customer

expected price = 30 - STEP(1,700) ~Dimensionless

line quality = 1 ~Dimensionless

MLM incentive = 1.5 ~$/customer

MLMers = INTEG (MLMization rate-obsolescing rate2,10) ~customers

MLMers' claim rate = 0.016 ~claim/customer/day

MLMization rate = (BmT regular customers * effect of incentive on MLMization)/contract delay ~customers/day

obsolescence delay = 3 ~day

price = 25 ~$

regular customers' claim rate = 0.006 ~claim/customer/day

Service claim = INTEG (claim rate-settlement rate,10) ~claim

settlement delay = Service claim/settlement rate ~day

Table of line on attractiveness(((0,0)-(5,2)),(0,0),(0.81571,0.72807),(1,1),(1.28399,1.25439),(5,2)) ~-Dimensionless

Table for incentive on MLMization(((0,0)-(10,1)),(0,0),(2.47734,0.0263158),(4.98489,0.127193),(7.49245,0.219298),(10,0.25)) ~Dimensionless

Table for obsolescing rate1(((0,0)-(8,1)),(0,1),(1,0.5),(8,0)) ~Dimensionless

Table for obsolescing rate2(((0,0)-(8,1)),(0,1),(1,0.2),(8,0)) ~Dimensionless

Table of delay on attractiveness(((0,0)-(10,2)),(0,2),(0.5,1.2),(1,1),(1.5,0.8),(10,0)) ~Dimensionless

Table of price on attractiveness(((0,0)-(5,2)),(0,2),(0.830816,1.35965),(1,1),(1.23867,0.719298),(2,0.5),(5,0.1)) ~Dimensionless

References

Ackoff, R. L., & Emery, F. E. (1972). On purposeful systems. Chicago IL: Aldine-Atherton.

Alavi, M., & Leidner, D. E. (2001). Review: knowledge management and knowledge management systems: conceptual foundation and research issues. *MIS Quarterly*, *25*(1), 107–136.

Alera, R., Borrajoa, D., Camachoa, D., & Sierra, A. (2002). A knowledge-based approach for business process reengineering, SHAMASH. *Knowledge-Based Systems*, *15*, 473–483.

Anderson, J. R. (1983). The architecture of cognition. Cambridge, MA: Harvard University Press.

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

Bass, B. (1983). Organizational decision making. Homewood, IL: Richard D. Irein Co.

Beach, L., Chi, M., Klein, G., Smith, P., & Vicente, K. (1997). Naturalistic decision making and related research lines. In C. Zsambok, & G. Klein (Eds.), *Naturalistic decision making*. Mahwah, NJ: Laurence Erlbaum Associates.

Bennett, R. H., III (1998). The important of tacit knowledge in strategic deliberations and decisions. *Management Decision*, *36*(9), 589–597.

Checkland, P. (1981). Systems thinking, systems practice. Wiley: Chichester.

Cheng, M. M., Luckett, P. F., & Schulz, A. D. (2003). The effects of cognitive style diversity on decision-making dyads: an empirical analysis in the context of a complex task. *Behavioral Research in Accounting*, *15*, 39–62.

Courtney, J. F. (2001). Decision making and knowledge management in inquiring organization: toward a new decision-making paradigm for DSS. *Decision Support Systems*, *31*, 17–38.

Daft, R., & Lengel, R. (1986). Organizational information requirements media richness, and structural design. *Management Science*, *32*, 554–571.

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

Davenport, T. H., Javenpaa, S. L., & Beers, M. C. (1996). Improving knowledge work process. *Sloan Management Review*, *37*(4), 53–65.

Dean, J., & Sharfman, M. (1993). Procedural rationality in the strategic decision-making process. *Journal of Management Studies*, *30*, 587–610.

Diffenbach, J. (1982). Influence diagrams for complex strategic issues. *Strategic Management Journal*, *3*, 133–146.

Earl, M. J., & Scott, I. A. (1999). What is a chief knowledge officer? *Sloan Management Review*, *40*(2), 29–38.

Eden, C., Ackerman, F., & Cropper, (1992). The analysis of cause maps. *Journal of Management Studies*, *29*(3), 309–324.

Edwards, E. (1961). Behavioral decision theory. *Annual Review of Psychology*, *12*, 473–498.

Edwards, J., Duan, Y., & Robins, P. (2000). An analysis of expert systems for business decision making at different levels and in different roles. *European Journal of Information Systems*, *9*, 36–46.

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

Ford, D. N., & Sterman, J. D. (1998). Expert knowledge elicitation to improve formal and mental models. *System Dynamics Review*, *14*(4), 309–340.

Forrester, J. W. (1961). Industrial dynamics. Portland, OR: Productivity Press.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: an organizational capabilities perspective. *Journal of Management Information Systems*, *18*(1), 185–214.

Gordon, E. G., & Gill, R. T. (1997). Cognitive task analysis. In C. Zsambok, & G. Klein (Eds.), *Naturalistic decision making*. Mahwah, NJ: Laurence Erlbaum Associates.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*, 109–122.

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

Hall, D. J., Paradice, D. B., & Courtney, J. G (2001). Creating feedback loops to Support Organizational learning and knowledge management in inquiring organizations. *Proceedings of the 34th HICSS*.

Hendriks, P., & Vriens, D. (1999). Knowledge-based systems and knowledge management: friends or foes? *Information and Management*, *69*(1), 113–122.

Hitt, M., & Tyler, B. (1991). Strategic decision models: integrating difference perspectives. *Strategic Management Journal*, *12*, 327–352.

Hutchins, E. (1995). Cognition in the world. Cambridge, MA: MIT Press.

Hoffman, R. R., Crandell, B., & Shadbolt, N. (1998). Use of critical decision method to elicit expert knowledge: a case study in the methodology of expert task analysis. *Human Factors*, *40*, 254–276.

Howard, R. A. (1989). Knowledge Maps. *Management Science*, *35*(8), 903–922.

Janis, I. L., & Mann, L. (1977). Decision making: A psychological analysis of conflict, choice, and commitment. New York: Free Press.

Kahneman, D., Slovic, P., & Tversky, A. (1982). Judgement under uncertainty: Heuristics and biased. Cambridge: Cambridge University Press.

Kim, D. H., & Senge, P. M. (1994). Putting systems thinking into practice. *System Dynamics Review*, *10*(2–3), 277–290.

Kim, Y. G., Yu, S. H., & Lee, J. H. (2003). Knowledge strategy planning: methodology and case. *Expert Systems with Application*, *24*, 295–307.

Klein, G. (1993). A recognition-primed decision (RPD) model of rapid decision making. In G. Klein, J. Orasanu, R. Calderwood, & C. E. Zsambok (Eds.), *Decision making in action: models and methods*. Norwood, CT: Albex.

Klein, G. (1999). Source of power: How people make decisions. Cambridge, MA: MIT Press.

Klein, J. H., & Cooper, D. F. (1982). Cognitive map of decision-makers in a complex game. *Journal of Operational Research*, *33*, 63–71.

Klein, G. A., Calerwood, R., & MacGregor, D. (1989). Critical decision method for eliciting knowledge. *IEEE Transactions on Systems, Man, and Cybernetics*, *19*, 462–472.

Knowledge Management Center, University of Texas, Austin (http://www.bus.utexas.edu/kman/).

Liebowitz, J. (1997). Knowledge-based/expert systems technology in life support systems. *Kybernetes*, *26*(5), 555.

Liebowitz, J. (2003). A set of frameworks to aid the project manager in conceptualizing and implementing knowledge management initiatives. *International Journal of Project Management*, *21*(3), 189.

Liebowitz, J., & Beckman, T. (1998). Knowledge organizations: What every manager should know. Boca Raton, FL: St. Lucie/CRC Press.

Liebowitz, J., Buchwalter, J., McCaw, D., et al. (2001). SMARTVision: a knowledge-management methodology. *Journal of Knowledge Management*, *5*(4), 300–310.

Lipshitz, R., & Bar-Ilan, O. (1996). How problems are solved: reconsidering the phase theorem. *Organization Behavior and Human Decision Processes*, *65*, 48–60.

Malhotra, Y. (2001). Expert systems for knowledge management: crossing the chasm between information processing and sensing making. *Expert System with Application*, *20*, 7–16.

Manzoni, J., & Angehrn, A. A. (1998). Understanding organisational dynamics of IT-enabled change: a multimedia simulation approach. *Journal of Management Information Systems*, *14*(3), 109–140.

March, J. G., & Shapira, Z. (1982). Behavioral decision theory and organization decision theory. In G. R. Ungson, & D. N. Braunstein (Eds.), *Decision making: An interdisciplinary inquiry, Boston, Kent* (pp. 92–115).

March, J. G., & Shapira, Z. (1987). Managerial perspectives on risk and risk taking. *Management Science*, *33*(11), 1404–1418.

March, J. G., & Simon, H. A. (1958). Organization. New York: Wiley.

Meehl, P. E. (1954). Clinical vs. statistical predictions: Theoretical analysis and review of the evidence. Minneapolis: University of Minnesota Press.

Meso, P., Troutt, M. D., & Rudnicka, R. F. (2002). A review of naturalistic decision making research with some implications for knowledge management. *Journal of Knowledge Management*, *6*(1), 63–73.

Mockler, R. J. (1989). Knowledge-based systems for management decisions. New Jersey: Prentice-Hall.

Mockler, R. J., & Dologite, D. G. (1992). Expert systems to support strategic management decision-making. In D. E. Hussey (Ed.), (*vol. 3*) (pp. 133–148). *International review of strategic management*.

Newell, A., & Simon, H. A. (1972). Human problem solving. Englewood Cliffs, NJ: Prentice-Hall.

Nonaka, I. (1991). The knowledge creating company. *Harvard Business Review*, *69*(6), 96–104.

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

O'Leary, D., & Turban, E. (1987). The organizational impact of expert systems. *Human Systems Management*, *7*(1), 11–19.

Ozbayrak, M., & Bell, R. (2003). A knowledge-based decision support system for the management fo parts and tools in FMS. *Decision Support Systems*, *35*, 487–515.

Peterson, D., & Eberlein, R. (1994). Reality check: a bridge between systems thinking and system dynamics. *System Dynamics Review*, *10*(10), 159–174.

Pylyshyn, Z. W. (1984). Computation and cognition. Cambridge, MA: MIT Press.

Ramaprasad, A., & Poon, E. (1985). A computerized interactive technique for mapping influence diagrams (MIND). *Strategic Management Journal*, *6*, 377–392.

Richardson, G (1983). The feedback concept in American social science, with implications for system dynamics. *International System Dynamics Conference, Massachusetts*.

Richardson, G. (1986). Problems with causal-loop diagrams. *System Dynamics Review*, *2*(2), 158–170.

Savage, L. J. (1954). The foundation of statistics. New York: Wiley.

Schmitt, N. (1997). Naturalistic decision making in business and industrial organizations. Mahwah, NJ: Laurence Erlbaum Associates.

Senge, P. M. (1990). The fifth discipline: The art and practice of the learning organisation. New York: The Doubleday Co.

Senge, P. M., & Sterman, J. D. (1992). Systems thinking and organisational learning: Acting locally and thinking globally in the organisation of the future. *European Journal of Operations Research*, *59*, 137–150.

Simon, H. A. (1978). Rationality as process and as product of thought. *American Economic Review*, *68*, 1–16.

Skraba, A., Kljajic, M., & Leskovar, R. (2003). Group exploration of systems dynamics model- is there a place for a feedback loop in the decision process? *System Dynamics Review*, *19*, 243–263.

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

Sterman, J. D. (1989). Misperceptions of feedback in dynamic decision making. *Organizational Behaviour and Human Decision Process*, *43*, 271–287.

Sterman, J. D. (1991). A skeptic's guide to computer models. In G. O. Barney (Ed.), *Managing a nation: The microcomputer software catalog* (pp. 209–229). Boulder, CO: Westview Press.

Sterman, J. D. (1994). Learning in and about complex systems. *System Dynamics Review*, *10*, 301–335.

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

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

Sternberg, (1997). Managerial intelligence: why IQ isn't enough. *Journal of Management*, *23*, 475–493.

Teece, D. T. (1998a). Capturing vale from knowledge assets: the new economy, markets for know-how, and intangible assets. *California Management Review*, *40*(3), 55–79.

Teece, D. T. (1998b). Research directions for knowledge management. *California Management Review*, *40*(3), 289–292.

Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological Review*, *55*, 189–208.

Wheatley, M. J. (2001). The real work of knowledge management. *IHIRM Journal*, *5*(2), 29–33.

Wiig, K. M. (1997). Knowledge management: where did it come from and where will it go? *Expert Systems with Applications*, *13*(1), 1–14.

Wong, B. K., & Monaco, J. A. (1995). Expert system application in business: a review and analysis of the literature (1977–1993). *Information and Management*, *29*(3), 141–152.

Zsambok, C. E. (1997). *Naturalistic decision making: where we now? Naturalistic decision making*, Mahwah, NJ: Laurence Erlbaum Associates.