ELSEVIER

Decision Support Systems 32 (2002) 297–309

Decision Support Systems

www.elsevier.com/locate/dsw

The enabling role of decision support systems in organizational learning

Ganesh Datt Bhatt, Jigish Zaveri*

Department of Information Science and Systems, 1700 E. Cold Spring Lane, Morgan State University, Baltimore, MD 21251, USA

Received in revised form 1 February 2001; accepted 1 August 2001

Abstract

Organizations routinely process information, make decisions, and implement them. Recent advances in computer and communications technologies have changed the way in which organizations perform these functions. Decision support systems (DSSs) are a major category of tools that an organization utilizes to support and enhance its decision-making activities. Traditionally, organizations are considered to have a predefined and static set of goals. However, in order to stay competitive and survive in today's dynamic environment, organizations must be able to quickly respond and adapt to changes in their business settings. Such changes could be due to technological advances, growing and changing customer demands, competitive forces, changes in the labor force, environmental and political concerns, societal impacts, security concerns, and others. In recent years, the field of DSS has become more sophisticated to encompass such paradigms as expert systems (ESs), intelligent DSSs, active DSSs, and adaptive DSSs. Artificial intelligence (AI)-based techniques are being embedded in many DSS applications, thus enhancing the support capabilities of the DSS. Such paradigms have application potential in both individual and organizational learning contexts. However, the degree to which current DSSs can support organizational learning has yet to be investigated in depth. This paper examines the learning strategies employed by organizations and DSSs and provides a framework to demonstrate how a DSS can enhance organizational learning. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Decision support systems; Adaptive DSSs; Organizational learning; Artificial intelligence; Inductive learning

1. Introduction

Drucker [17] observed that the world is entering a post-industrial era in which availability and processing of information will become critical. Hence, organizations whose structures, processes, and technologies are not well suited to deal with the increasing environmental complexity and knowledge are unlikely to survive [32]. In order to survive and thrive in these ever increasing competitive markets and complex environments, organizations must continually learn and process new skills, knowledge, and routines about products, processes, and social relations.

Argyris and Schon [3] defines organizational learning as a process of detecting and correcting errors so that organizations are able to function and realize their goals and objectives. If organizations do not learn and adapt to their ever-changing environments, they face prospects of eroding their competitiveness and eventually, maybe, extinction.

* Corresponding author. Tel.: +1-443-885-3738.
E-mail addresses: gbhatt@morgan.edu (G.D. Bhatt), jzaveri@morgan.edu (J. Zaveri).

0167-9236/02/$ - see front matter
PII: S0167-9236(01)00120-8

Exploration and controlled experimentation are essential factors of the learning process. One of the key factors that permits an organizational actor or a decision maker (DM) to take risks and seek varieties is directly related to the DM's personal preference and choice. Decision support systems (DSSs) can play a major role in enhancing the DM's decision-making abilities. In recent years, the field of DSS has become more sophisticated to encompass such paradigms as expert systems (ESs), intelligent DSSs, active DSSs, and adaptive DSSs. Such paradigms have application potential in both individual and organizational learning contexts. However, the degree and depth to which current DSSs supports organizational learning has yet to be investigated. This paper examines the learning strategies employed by DSSs and provides a framework to demonstrate how a DSS can support and enhance organizational learning. DSSs can support and enhance a DM's decision-making capabilities by processing data and allowing participants to simulate a variety of scenarios quickly and make effective decisions in an efficient manner. A DSS can also help to assess and compare the benefits and risks of exploration within the organization [32].

In spite of mutual linkages between the DSS and organizational learning, the concept of how a DSS can enhance and facilitate organizational learning has not been explored. This paper examines the learning strategies employed by DSSs and organizations and discusses different kinds of DSSs that can facilitate, promote, and enhance organizational learning. We believe this paper will be useful in providing guidance to managers, as managers in different companies are enamored by the concept of organizational learning and are looking for new ways to enhance and promote learning in their organizations. This paper also provides insights and an overview for researchers exploring the relationship between DSSs and organizational learning. The rest of the paper is organized as follows. In Section 2, we briefly discuss organizational learning and the nature of the resultant expertise. In Section 3, we present the different functions and characteristics of DSSs. In Section 4, we discuss the different DSS paradigms in terms of their underlying learning strategies to acquire and reorganize its knowledge and thus enhance the organization's performance. In this section, we also discuss the different ways in which DSSs can facilitate, support, and enhance learning in organizations. In Section 5, we highlight the key attributes of DSSs that can promote and enable organizational learning. Section 6 discusses the potential future of using DSSs to facilitate and enhance organizational learning and Section 7 contains concluding remarks.

2. Organizational learning

Since the mid- and late-1980s, the subject of organizational learning has gained considerable attention among academicians and practicing managers. The importance of organizational learning can be attributed to the ever-changing, dynamic, and complex business environments. The way in which organizations acquire new skills and knowledge and at the same time exploit useful and discard obsolete and anarchic existing knowledge is a subject of inquiry [56].

Learning is considered necessary for knowledge creation. However, learning does not guarantee that knowledge learnt is useful and adaptive to the environments. In fact, exploitation of past knowledge can be useful only to the point when environments remain stable. If environments start changing, learning of existing rules and technologies can be an overhead to the organization and its members. It is very difficult to unlearn a well-learned program and/or method and start over with a new set of skills and learn new programs. Since knowledge creation is a dynamic process, unlearning existing programs and learning new sets of capabilities often become essential.

Organizations need to learn because they are open systems. They continually interact with external environments to sustain their long-term viability. If organizations act as closed systems, their long-term survival becomes questionable when environments change unpredictably. In an organization, however, not all organizational members interact in a similar fashion. Each of these individuals may have different, if not conflicting, views and may construct different models about the organization and its environments leading to incompatibility among these models and eventually the organization may not be able to realize its full potential. This is because organizational learning is not a simple aggregate sum of individual learning but is an exchange and sharing of individual assumptions and models throughout the organization.

Argyris and Schon [3] have identified two types of learning mechanisms used by organizations: single-loop and double-loop learning. In single-loop learning, error detection is important. This implies that based on the feedback loop, organizational members take necessary actions to control variance. The feedback loop is linked directly with the outcomes, strategies, and assumptions about the organization and environments. In a more or less stable environment, single-loop learning is considered efficient, because its main objective is to achieve planned goals and performance targets within an acceptable range [57].

Double-loop learning, on the other hand, involves revisions of assumptions, guidelines, and underlying objectives of an organization. By questioning existing routines and assumptions about the organization and its environments, many incompatibilities are resolved or, at best, uncovered. This type of learning is difficult because people do not want to be challenged about their assumptions, guidelines, and understanding of the organization's norms and policies. However, if an organization begins to transform itself, it starts uncovering existing assumptions and goals about the organization and environments that are not consistent and embarks on forming new sets of assumptions, guidelines, and beliefs [57].

In a narrow sense, Argyris and Schon [3] refer to single-loop learning as problem solving, whereas double-loop learning is critical reflection leading to further learning. The authors contend that most organizations tend to follow single-loop learning, which involves the detection and correction of organizational error, but permits the organization to carry on its present policies to achieve its current objectives. Alternatively, very few organizations follow double-loop learning that involves the detection and correction of errors by modifying the underlying norms, policies, objectives, and operating assumptions. In a broader sense, we can say that single-loop learning is the one that maintains the organization, whereas double-loop learning is the one that redefines an organization enabling it to adapt and survive in dynamic environments.

One of the key requirements in organizational learning is the exchange and sharing of assumptions, guidelines, and beliefs about the organization and environments. To exchange and share key assumptions and beliefs, information about assumptions and beliefs should be acquired, distributed, and interpreted. Huber [32] identified four constructs: information acquisition, information distribution, in-formation interpretation, and organizational memory, as integral elements of organizational learning. Organizations acquire, distribute, and interpret information in various ways. By scanning, searching, and monitoring its external environment, an organization maintains its alignment with the external environments. For instance, an organization may closely monitor the design mix of its competitors' products and the expectations of customers.

Information acquisition refers to collection of relevant information from internal and external sources. Organizations employ several mechanisms such as use of boundary spanners, organizational structure, information systems, informal communications, and others to collect information. By scanning and searching internal and external environments, organizations can detect environmental signals for setting their priorities and strategies [18].

Distribution of information, more than often, cuts across functional boundaries causing difficulties in dealing with autonomous decisions. It is not always easy to come to a consensus on the definition and the solution of a problem when problems and their solutions directly affect a number of links. Organizations require coordinating their resources to assimilate their ideas and knowledge for the solution of the problems. The distribution of information, however, raises an important question for several managers, who find it hard to accommodate different views. Such managers often keep important information to themselves and may not disclose any information from their side [12]. For example, most organizations are required to create many informal channels of communication among its design, manufacturing, and marketing departments [2]. The employment of concurrent engineering to introduce new and error-free products to customers, is a widely used technique of increasing information distribution among various members in the organization [32].

Information interpretation is considered critical for organizational learning. Alternatively, the way in which organizational members give a *meaning* to information is quite debatable [6,66]. Depending on the context, organizational members may offer different interpretations to same or similar information. For bringing divergent opinions and meanings to the surface, organizations are required to continually update their knowledge sources.

Organizational memory enables organizations to quickly respond to crisis and make efficient and effective adjustment to the conflicting demands of the environments. However, when organizational environments change rapidly, the use of organizational memory cannot always provide predictable and useful solutions. In these cases, an organization should continuously refine and update its memory [64].

3. Decision support systems

In the simplest sense, a DSS is a computer software that facilitates and accepts inputs of a large number of facts and methods to convert them into meaningful comparisons, graphs, and trends that can facilitate and enhance a decision makers' (DMs) decision-making abilities. A DSS can assist a DM in processing, assessing, categorizing, and/or organizing information in a useful fashion that can be easily retrieved in different forms. Additionally, a DSS can also assist in monitoring and tracking organization performance based on the organization's goals and objectives.

Using computer-assisted tools, management can effectively and efficiently process data to gain knowledge and meaningful patterns [37]. Further, Keen [36] ascertains that the DSS user, the DSS builder, and the DSS influence each other during the design, construction, and implementation phases of the DSS that is developed through an adaptive process of learning and evolution. Thus, a DSS is a system that alters its knowledge base of facts and methodologies to be consistent with the ever-changing external environments and internal structures of organizations. A DSS can also assist in monitoring decision processes, alerting users of their inconsistent assumptions, and in making context-based decisions.

A well-designed DSS can facilitate problem solving and enhance the organizational learning process. A DSS can facilitate problem recognition, model building, assist in collecting, integrating, organizing, and presenting the relevant knowledge, select an appropriate problem solving strategy, evaluate the different solutions, and choose the *best* solution. All these activities can promote organizational learning, making it a more efficient, effective, and a satisfying process. Additionally, a DSS can also be helpful in implementation and evaluation of the selected strategy.

The two key subsystems of a DSS are its knowledge system (KS) and its problem processing system (PPS) that significantly impact its problem-processing behavior. From the perspective of DSSs, change in the state of knowledge in its KS is synonymous with learning. The KS constitute problem processing knowledge (PPK) of the DSS, procedures on how to utilize PPK, reasoning about why a certain piece of PPK is used, and environmental knowledge about the objective, constraints, and the domain of the problem [28].

Depending on the objectives, constraints, and domain of the problems, the system works on input information to generate new knowledge, which is stored in its KS. In subsequent iterations of the problem solving process, the useful generated knowledge may provide more meaningful knowledge. A DSS may employ any of the several machine learning strategies to discover new knowledge during its problem solving exercise. The major intent of this is to incorporate new and potentially more useful and meaningful knowledge in its KS and PPS to influence and improve its subsequent problem-processing behavior [46]. In the following section, we discuss the different DSS paradigms in the context of the learning strategies it employs. In this section, we also briefly discuss the ways in which DSSs can facilitate, promote, and enhance learning in organizations.

4. DSS paradigms and learning strategies

Machine learning techniques utilized by DSSs can enhance their capabilities for discovering new information and processes. Intelligent technology is widely integrated in organizations where human and machines can interact with each other to learn and sharpen their problem solving skills. Additionally, both human and machine learning can be viewed as having common goals of knowledge and skills acquisition with the intent of improving future performance. A DSS equipped with one or more of the following machine learning techniques can greatly enhance its problem processing behavior and thus influence the organizational learning process.

Numerous machine learning strategies have been identified in the machine learning literature [9,48, 49,60]. For the purposes of this discussion, they can be broadly classified as learning by rote, learning by deduction, learning by analogy, and learning by induction. Learning by induction can further be categorized into supervised learning and unsupervised learning [29].

One of the key concerns in machine learning is that machines should be considerably faster in performing some learning activities [61]. Efficiency of machine learning is usually dependent on the kinds of learning activities and the development language. For example, a system that learns by rote is very efficient but is usually incapable of making any inferences. At the other extreme, a system that learns via induction maybe inefficient, but can be beneficial in novel situations where a DM does not have requisite knowledge to address the problem at hand. Such systems can prove to be extremely effective where available knowledge is minimal but expected to grow.

In the case of a rote learning system, the main emphasis is on memory and development of indexing schemes for efficient retrieval of stored knowledge. Therefore, in an organizational unit where most of the jobs and tasks are administrative and routine specific, a system that learns by rote can be very useful. These kinds of systems are conventional DSSs that can be preprogrammed to perform specific routine activities in a systematic and consistent fashion. In most cases, all of their problems processing facilities are built in at design time. The application program could repeatedly be invoked to correctly solve the pre-specified problem. The system does not become more effective or efficient in its abilities with repeated problem solving. The problem processor is invariant, which executes the stored instructions based on user directions. In a simple term, this kind of learning can be thought as passive learning. In essence, conventional DSSs acquire their PPK through rote learning to conduct their problem solving tasks. However, such systems can be designed to collect and present feedback information in a fashion that the DM can use to alter the behavior of the DSS with the aim of improving its subsequent performance.

A somewhat similar, yet sophisticated role is played by typical expert systems (ESs) which utilize deductive learning. The major goals in the design of ESs are to capture and represent the expertise of expert(s) so that it could be used by non-experts to enhance their productivity and improve the quality of their solutions [7]. The purpose of ESs is not to replace the expert but to free up the expert to address more complex issues [63]. By employing deductive reasoning, an ES can transform existing knowledge and reasoning laws derived from experts into useful representations, even though, it generally is not capable of generating new rules of inferences. In this sense, an expert system can also be viewed as a system that relies on rote learning. However, a more complex system integrated with an intelligent editor for instruction purposes and deriving new knowledge is an example of deductive learning. These systems have the ability to change its PPK based on the feedback it receives through numerous problem-solving exercises.

Thus, conventional DSSs can assist in solving problems at lower levels of management while ESs can aid in solving problems requiring use of the experts knowledge. However, both can support the construct of organizational memory and thus greatly influence the single-loop learning of organizations. Additionally, these DSSs and ESs can also be pre-programmed to identify and alert the user of the inconsistent assumptions made during a problem solving scenario and highlight conflicting objectives and policies of the organization. Thus, in a narrow sense, such systems can also influence double-loop learning in organizations.

Another paradigm suggests integrating model-oriented DSSs and ESs to create intelligent support systems that have been called integrated decision support-expert systems (DS-ESs) [30]. While such integration can take on a variety of forms, the highest potential benefit may be offered by allowing a set of ES components to provide expert-level support to the DSS model-based component of the integrated system. A representative example of an integrated DS-ES is the Police Patrol Scheduling System [62], where the problem processor is enhanced with ES capabilities.

A system that learns through analogies makes use of inference. However, inferences are based on common analogies that a system is aware of. These kinds of systems can be useful among the inter-organizational business units, as they can provide more integrated and a holistic view of the situation. More recently, some researchers have suggested a framework for learning through analogies [42]. Lessons learnt and insights obtained during one problem solving exercise can be applied to other similar scenarios. For example, Garvin [20] discusses the case of Boeing that compared the developmental process of its problematic launches of 737 and 747 with those of its more successful planes 707 and 727. Based on this comparison, Boeing was able to come up with recommendations that were used in the developmental process of 757 and 767—the most successful and error-free launches of planes in its history thus far.

Hwang [33] views intelligence in a DSS from a purely model-oriented perspective with the emphasis on two broad categories of models. First, in the absence of any traditional analytical modeling approaches for a decision problem, a DM may rely on an expert's reasoning knowledge about the problem domain to construct an artificial intelligence (AI)-based judgmental model. However, if a decision problem is susceptible to analytical modeling, then a DM can rely on someone versed in management science/operations research (MS/OR) to construct a procedural model. In this event, the MS/OR consultant is the domain expert. Both types of modeling knowledge may be captured and stored within a support system's KS for subsequent use.

Based on these considerations, Hwang proposes the development of an intelligent DSS as one that (i) analyzes a problem and identifies a solution approach, (ii) constructs or searches for an appropriate decision model (i.e., a judgmental model or an analytical model), (iii) executes this model, and (iv) interprets the solution and "learns from the experience". The system is largely an expert mathematical modeling consultant.

Other advances in DSSs have simulated frameworks for the development of active DSSs. The idea behind the system is that it can work independent of the need of the directions by the users [45]. The system can learn without supervision because of its capabilities in storing past knowledge and rules about particular problems in its knowledge base, and such systems are adaptive enough to change the processing model if users understanding of the problem changes. By offering simple directions about problems and background information, these systems can independently generate and evaluate solutions of the problems. Such systems can support the constructs of knowledge acquisition and interpretation.

On the other hand, a system that learns through induction makes extreme use of inference. Based on this, Holsapple et al. [29] propose an adaptive DSS that utilizes unsupervised inductive learning to increase its knowledge. The main emphasis in this kind of learning is to develop systems that can scan and analyze relevant environment to make inference on new information. The goal here becomes much more complex. Systems should be able to not only learn from new information, but also be able to integrate new knowledge with the existing knowledge and be able to reorganize their knowledge base to improve performance. Therefore, in an organizational unit, which mostly deals with novel situations, a system that learns through induction can prove to be immensely useful. Hence, an adaptive DSS that utilizes this learning mechanism can not only enhance the single-loop learning, but can also greatly influence double-loop learning of organizations.

Many manifestations of the unsupervised inductive learning paradigm exist (for example, see Refs. [40,48,49,60]). Here, we briefly discuss four techniques that have been successfully applied to real world problems.

Simulated annealing [26,39] is an example of an unsupervised inductive learning technique that exploits the analogy between the fields of statistical mechanics and combinatorial optimization. Metropolis et al. [47] first proposed the technique as a means for generating feasible and stable configurations of atoms in a substance, at a given temperature. Subsequently, many researchers have studied the application of this idea in resolving many NP-complete problems within the field of optimization. For example, Kirkpatrick et al. [39], Kirkpatrick [38], Cerney [10], and Aarts et al. [1] address the travelling salesman problem using the technique.

Tabu search [23,24] is an unsupervised learning method that utilizes a set of operators to guide a process from one state to another. Tabu Search operates with a dynamic set of operators. Based on past historical data, this set consists of a set of tabu restrictions that classify certain moves as prohibited moves, together with a set of aspiration criteria capable of overriding (as appropriate) the tabu status of some moves and releasing them from this status. de Werra and Hertz [16], Glover and Greenberg [24], and Glover [23] have used the technique to address several combinatorial optimization problems, such as the travelling salesman, job flow shop sequencing, and graph coloring.

The technique of genetics-based machine learning draws on Holland's [27] seminal ideas about a class of algorithms called genetic algorithms (GAs). In nature, a combination of natural selection and procreation permits the development of living species that are highly adapted to their environments. A GA is an algorithm that operates on a similar principle. When applied to a problem, this algorithm uses a genetics-based mechanism to iteratively generate new solutions from currently available solutions. It then replaces some or all of the existing members of the current solution pool with the newly created members. The motivation behind the approach is that the quality of the solution pool should improve with the passage of time, a process much like the "survival of the fittest" principle that nature seems to follow. Numerous studies on the application of various kinds of GA-based approaches to computationally hard optimization problems from diverse domains include communications network configuration [13], gas and oil pipeline operations [22], image registration [25], surveillance in warfare [41], multi-stage flow shop scheduling [11,68], multi-objective work force scheduling [26], and the scheduling of limited resources in flexible manufacturing systems [28,53].

Artificial Neural Network (ANN) is a technique that focuses on designing and implementing computer systems with architectures and processing capabilities based on the processing capabilities of the human brain. It is a model that tries to mimic the biological neural network. An ANN is composed of processing elements or neurons that receives inputs, processes them, and produces an output that can be the final product (decision) or can serve as an input to another neuron. Turban and Aronson [63] assert that this results in ANNs using knowledge representation techniques that lends itself to massive parallel processing, quick retrieval and processing of large quantities of data, and effective and efficient pattern recognition based on past historical data. ANNs require training data for adjusting the weights or strengthening the connections between the neurons. Back-error propagation is the learning algorithm used by most ANNs [19]. ANNs have been used to provide complex decision support [59,65] and to solve many complex problems [5]. Poh [54] studied the use of ANN in strategic management and demonstrates the ease with which the ANN can conduct sensitivity analysis and partial analysis of input factors.

Marakas [46] points to a number of successful projects that have used ANN technology. For example, Nippon Steel Corporation has built a blast furnace operation control system using an ANN. The ANN learns the relationship between sensor data and different temperature patterns known from experience of the overall operation of the furnace. The use of ANN has provided a better perspective of the operation of the furnace and because of its excellent success rate Nippon Steel plans to introduce ANN technology into other operations of the blast furnace such as diagnosis of malfunctions. Similarly, Daiwa Securities Company and Nippon Electric Company (NEC) are using ANN technology to learn the future stock prices by analyzing the stock price chart patterns [46].

An adaptive DSS equipped with any of the unsupervised inductive learning mechanisms can support all the four integral components of organizational learning. As discussed, these DSSs can prove to be valuable in discovering knowledge, interpret the knowledge and classify them as useful and store them for future problem solving scenarios. They also have the capability to organize this knowledge for efficient retrieval, test its worth, and over a period of time discard any obsolete knowledge. Hence, they can assist the DM in discovering new and potentially useful knowledge and provide fresh insights with respect to the DM's understanding of the organization's assumptions, norms, and policies. Thus, besides influencing single-loop learning, such DSSs have a great potential in influencing double-loop learning in organizations.

We have discussed how DSSs can greatly assist in strengthening a DM's decision-making capabilities. Additionally, a DSS incorporating any of the learning capabilities discussed earlier can also increase the effectiveness of these decisions and the efficiency with which they can be implemented. In the following section, we discuss the key attributes of DSSs that facilitate, enhance, and thus enable and promote organizational learning.

5. DSS attributes enabling organizational learning

If organization members can reach on an agreement by disseminating and sharing information, the decision outcome is generally understood better [43,44]. Hence, the DSS should be designed to facilitate an understanding among different decision-making participants. The aim to reach a common understanding is much more important than the criteria of efficiency and effectiveness [14,15,55]. The attempt to reach a common understanding presupposes a symmetrical distribution of information among participants. With a common understanding among DMs, DMs have the opportunity to express their interpretation, claims, and explanations to be resolved with reciprocal claims and counter claims.

This understanding provides the means to DMs to express their interests, cognitive biases, and personal preferences. This allows DMs equal freedom to express themselves freely and posit their views and experiences. For example, Hsu [31] studied the effects of cognitive styles and interface designs on the use of knowledge-based systems (KBS) and focused on knowledge transfer from KBS to novice users. He observed that the availability of explanations was instrumental in learning of new knowledge to novice users and that the use of "justification" resulted in a greater amount of knowledge transfer than using explanations alone. There are a number of ways through which a DSS can enhance and facilitate the process of organizational learning. These are discussed next.

5.1. Efficient access of data

The performance of a DM will generally improve, if knowledge and the models are partitioned into frequently accessed and non-accessed domains based on the usage pattern of the DM. The frequency of retrieving particular pieces of knowledge and models depend on the biases of the DM. Although a DSS can improve individual biases by providing statistical and probability functions and introducing multiple alternatives, the DM still prefers a few models that match his/her mental processes of decision-making. For example, if DMs are more judgmental, DMs can first make judgments and then verify and validate them with the DSS models. For these users, it is important that they easily find those models that they frequently use in their judgments. On the other hand, for analytical DMs, the probability of using each model may be equal and the DM does not have any biases. Thus, models should be so positioned so they could be explored equally.

5.2. Experimentation with variables

Experimentation offers many advantages to managers to change their frame of reference. Managers who are willing to look beyond the normal scope of variables are ready to learn and test the validity of their assumptions [52]. By using *what-if* analysis and experimenting with different future scenarios, managers can evaluate, test, and modify their thinking patterns and judgments/decisions. Using different models, managers can eliminate biases and make appropriate and necessary modifications to their decisions.

5.3. Generation of alternate models

DSSs can also be used to create alternate models by generating new and creative ideas in different contexts. For example, a flexible DSS can often permit to increase or decrease the number of variables. By varying the number of variables, managers can often experiment and simulate different future scenarios [69]. These models help a DM in searching and making alternative perspectives and solutions. DSSs that have the capabilities to support multiple schemata and provide necessary guidance in structuring and simplifying the problems can be of immense use in heuristic problems to help DMs looking beyond the obvious solutions.

5.4. Trend analysis

Adaptive DSSs, equipped with inductive learning mechanisms and statistical methods, can assist an organization in interpreting different data patterns and forecast the organizational readiness for seasonal growth and productivity. For example, trend analysis is relevant to travel and tourism industries, which need to deal with seasonal ups and downs. Armed with trend analysis, an organization is better able to forecast and take proactive actions.

5.5. Exploratory and confirmatory models

A DSS incorporating different levels of exploratory and confirmatory models should match DMs' expertise. Novice users do not like the use of complex models, but on the other hand, experts do not prefer the drill down approach for the finer analysis of the problems. For example, novice users mostly drill down at each level of the menu structure, while experts mostly go to the command mode directly. Therefore, a DSS, with its aim to increase organizational learning, should employ both types of interfaces: graphical user interfaces as well as command mode of instructions.

5.6. Simulation

DSSs can support simulation studies, which are essential for reducing ambiguity and uncertainty. By using different scenarios, a DSS enables an organization to comprehend the likely future realities and take necessary proactive action. By simulating different scenarios, organizational members can interpret future environments in the similar light, which is often considered important to assimilating individual based learning to organizational learning. Computerized simulations are explicit, and hence their results can easily be transferred throughout the organization. A DSS armed with the inductive learning capabilities can generate and simulate different scenarios to explore and test different conditions and situations quickly and economically. More recently, Ninios et al. [51] have used the object-oriented approach to develop simulation models.

5.7. Justification of solutions

By making the details of solutions clear, a DSS can help in improving DMs understanding and clearly visualize the role of different variables in the decision-making [58]. The manipulations of different models, existing and transformed ones, can help in creating awareness among organizational members to facilitate the changes as a result of the systems use. For example, a key feature of ESs is its ability to provide justification for its conclusions and/or advice. This feature of ESs enables it to explain its behavior, to identify the knowledge used, and to trace back the steps that were taken in arriving at a specific conclusion. Based on this feedback, modifications can be made to refine the systems' knowledge base and/or alter its inferencing mechanism. The intent of this is to alter the behavior of the system to address more complex problems effectively.

5.8. Exploration vs. exploitation of knowledge

A DSS enables organizations to exploit past historical knowledge. The database component of a DSS is a rich source of historical data [30]. The database component may include data from external sources regarding its environment and internal sources regarding the organizations' resources, capabilities, and performance. The periodical evaluation of database offers an organization the opportunities to exploit the potential sources of competitive advantages. Additionally, the comparison of data over different times, sites, and locations can assist an organization to evaluate its performance over different periods, locations, and sites.

5.9. Idea generation

To gain a competitive edge, the current trend for organizations is to go global. The major challenge faced by these organizations is to facilitate efficient and effective teamwork [4]. The use of Group DSSs (GDSSs) can facilitate participants to come together and share their views by reducing the constraints of time and place. An organization equipped with a GDSS is better able to utilize the knowledge of its employees by sharing information and complementary knowledge [35]. For example, by using groupware tools, CIGNA was able to share the expertise of its employees spread across 55 international units [8].

6. Future implications

In this study, we have shown how DSS can enhance organizational learning. With the increasing use of powerful computers and standard telecommunications, we envision a trend in which DSSs will be increasingly used for enhancing organizational learning. This is especially true in the arena of electronic commerce (e-commerce) where organizations are facing a turbulent environment and are pressed to quickly adapt to the changing environment. In order to deal with such dynamic environments, organizations will increasingly make the use of intelligent agents that will facilitate both single-loop learning and double-loop learning. Some of these intelligent and autonomous agents like SodaBot and Foner Agents can help in negotiations, group collaboration, and dialog generation. Similarly, other agents like Maes, KidSim, IBM, and Hayes–Roth Agents assist in identifying problems in dynamic environments, offering solutions, and accomplishing the tasks autonomously [46].

Janca [34] argues that in the near future intelligent agents will play critical roles and greatly impact an organization's performance. By using these software agents on their desktop computers, users can easily take advantages of the capabilities of these tools as they assist users both in sorting the information and data mining. Hence, instead of receiving an overwhelming load of information, users will receive only the relevant information that they are most likely to use in making decisions.

In addition, organizations will make use of DSSs for dynamic modeling that would provide several opportunities for scenario planning and sensitivity analysis [46]. Also, increasing use of communication networks will allow organizations to make use of GDSSs for brainstorming, collaboration, information sharing, and communication purposes. By using GDSSs, participants in one or more teams in the organization will capitalize on the opportunities for learning from each other [21]. Marakas [46] has shown that GDSSs have been extremely useful in generating a long list of ideas efficiently. For example, brainstorming can be incorporated in DSSs as stand-alone modules or as a part of guided processes [46]. Moffitt [50] argues that the intelligent agents, which contain explanation facilities, can enhance trust between computer users and their "intelligent agents".

7. Conclusions

In this paper, we have proposed ways in which DSSs can facilitate, promote, enhance, and support organizational learning. In current dynamic environments, the potential of DSSs for enhancing organizational learning can be even more important. For example, when decision-makers are faced with making quick ad-hoc decisions, a DSS can provide efficient and effective modeling capabilities. Using these GDSSs, managers can easily communicate their decisions across the hierarchies. This helps in bringing organizational members together for creating a mental schema of the problem and its solution [66,67].

A well-designed DSS provides managers with the options to check and evaluate different mental schemas and their outcomes. This usually results in managers selecting the best solution consistent with their organization's overall goals and mission. The validation of models through a DSS can be useful, as it will usually provide the same decision in the same contexts. If users and other organizational members can check and validate the accuracy of their decisions through a DSS, they usually become aware of the critical variables and contexts in which a particular decision is made. In essence, different DSS paradigms, ranging from a conventional DSS to adaptive DSS, can potentially influence both single-loop as well as double-loop learning in organizations.

A DSS is a tool of self-expression and explanation for the DM. Self-expressions and explanations not only require flexibility in the use of the DSS, but also a sense of direct control over the DSS. The flexibility of the DSS can be managed by easy to work user interfaces and easy modeling capabilities. Confirming the conceptual models of the DMs with the DSS models can provide the control over the DSS. This compatibility between the DM and the DSS provides a direct opportunity to the DM to evaluate the operations of the DSS and integrate the information provided by the DSS with information provided by the other sources. Additional research needs to be done to examine, in detail, the issues and criteria that will help identify the appropriate DSS(s) that will promote organizational learning. In general, in complex situations, where humans are unable to analyze the effect of the several interacting variables simultaneously, a DSS can provide a better perspective of their interactions and the corresponding solution by offering its data mining, modeling, and analytical capabilities.

References

[1] E.H.L. Aarts, J.H.M. Korst, P.J.M. Van Laarhoven, A quantitative analysis of the simulated annealing algorithm: a case study for the travelling salesman problem, Journal of Statistical Physics 50 (1988) 189–206.

[2] S.L. Alter, Decision Support Systems, Current Practice and Continuing Challenges, Addison-Wesley, Reading, MA, 1980.
[3] C. Argyris, D.A. Schon, Organization Learning, Prentice-Hall, Englewood Cliffs, NJ, 1978.
[4] H. Axel, Company experiences with global teams, HR Executive Review 4 (1996) 3–18.
[5] B. Back, T. Laitinen, K. Sere, Neural networks and genetic algorithms for bankruptcy predictions, Expert Systems with Applications 11 (1996).
[6] J.M. Bartunek, Changing interpretive schemes and organizational restructuring: the example of a religious order, Administrative Science Quarterly 29 (1984) 355–372.
[7] R.H. Bonczek, C.W. Holsapple, A.B. Whinston, Future directions for developing decision support systems, Decision Sciences (1980) 616–631.
[8] M. Boudreau, K.D. Loch, D. Robey, D. Straud, Going global: using information technology to advance the competitiveness of the virtual transnational organization, Academy of Management Executive 12 (1998) 120–128.
[9] J.G. Carbonell, R.S. Michalski, T.M. Mitchell, An overview of machine learning, in: R.S. Michalski, J.G. Carbonell, T.M. Mitchell (Eds.), Machine Learning: An Artificial Intelligence Approach, vol. 1, Morgan Kaufmann, San Mateo, CA, 1983.
[10] V. Cerney, A thermodynamic approach to the travelling salesman problem: an efficient simulation algorithm, Journal of Optimization Theory and Applications 45 (1985) 41–51.
[11] G.A. Cleveland, S.F. Smith, Using genetic algorithms to schedule flow shop releases, in: D. Schaffer (Ed.), Proceedings of the Third International Conference on Genetic Algorithms, San Mateo, CA, 1989, pp. 160–169.
[12] T.H. Davenport, Saving its soul: human-centered information management, Harvard Business Review 72 (1994) 119–131.
[13] L. Davis, S. Coombs, Optimizing network link sizes with genetic algorithms, in: M. Elzas, T. Oren, B.P. Zeigler (Eds.), Modelling and Simulation Methodology: Knowledge Systems Paradigms, North-Holland, Amsterdam, 1989.
[14] S. Deetz, Conceptualizing human understanding: Gadamer's hermeneutics and american communication research, Communication Quarterly 26 (1978) 12–23.
[15] S. Deetz, Representation of interests and new communication technologies: issues in democracy and policy, in: M.J. Medhurst, A. Gonzalez, T.R. Peterson (Eds.), Communication and the Culture of Technology, Washington State Univ. Press, Washington, 1990.
[16] D. de Werra, A. Hertz, Tabu search techniques: a tutorial and an application to neural networks, Operations Research Spectrum 11 (1989) 131–141.
[17] P.F. Drucker, Innovation and Entrepreneurship, Harper & Row, New York, 1985.
[18] J.E. Ettlie, Product-process development integration in manufacturing, Management Science 41 (1995) 1224–1237.
[19] L.V. Fausett, Fundamentals of Neural Networks: Architecture, Algorithm, and Applications, Prentice-Hall, New Jersey, 1994.
[20] D.A. Garvin, Building a learning organization, Harvard Business Review 71 (1993) 78–91.
[21] J.F. George, The conceptualization and development of organizational decision support systems, Journal of Management Information Systems 8 (1991) 109–125.
[22] D.E. Goldberg, C.H. Kuo, Genetic algorithms in pipeline optimization, Journal of Computing in Civil Engineering 1 (1987) 128–141.
[23] F. Glover, Tabu search—Part II, ORSA Journal on Computing 2 (1990) 4–32.
[24] F. Glover, H.J. Greenberg, New approaches for heuristic search: a bilateral linkage with artificial intelligence, European Journal of Operations Research 39 (1989) 119–130.
[25] J.J. Grefenstette, J.M. Fitzpatrick, Genetic search with approximate function evaluations, Proceedings of an International Conference on Genetic Algorithms and Their Applications, Hillsdale, New Jersey, Lawrence Erlbaum Associates, 1985, pp. 112–120.
[26] M.R. Hilliard, G.E. Liepins, G. Rangarajan, M. Palmer, Learning decision rules for scheduling problems: a classifier hybrid approach, Proceedings of the Sixth International Conference on Machine Learning, San Mateo, CA, Morgan Kaufmann, 1989, pp. 188–200.
[27] J.H. Holland, Adaptation in Natural and Artificial Systems, The University of Michigan Press, Michigan, 1975.
[28] C.W. Holsapple, V.S. Jacob, R. Pakath, J.S. Zaveri, Learning by problem processors: adaptive decision support systems, Decision Support Systems 10 (1993) 85–108.
[29] C.W. Holsapple, V.S. Jacob, R. Pakath, J.S. Zaveri, A genetics-based hybrid scheduler for generating static schedules in flexible manufacturing contexts, IEEE Transactions on Systems, Man, and Cybernetics 23 (1994) 953–972.
[30] C.W. Holsapple, A.B. Whinston, Guidelines for DBMS selections, in: C.W. Holsapple, A.B. Whinstone (Eds.), Data Base Management: Theory and Applications, Reidel, Dordrecht, Holland, 1983, pp. 367–387.
[31] K.C. Hsu, The effects of cognitive styles and interface design on expert systems usage: an assessment of knowledge transfer, PhD Dissertation, Memphis State University, 1993.
[32] G.P. Huber, Organizational learning: the contributing processes and the literatures, Organization Science 2 (1991) 88–115.
[33] S. Hwang, Automatic model building systems: a survey, Proceedings of the 1985 DSS Conference, 1985, pp. 22–32.
[34] P. Janca, Intelligent Agents: Technology and Application, GiGa Information Group, Norwell, MA, 1996.
[35] P.G.W. Keen, Every Manager's Guide to Information Technology, Harvard Business School Press, Boston, 1995.
[36] P.G.W. Keen, Decision support systems: translating useful models into usable technologies, Sloan Management Review 21 (1980) 33–44.
[37] P.G.W. Keen, M.S. Scott-Morton, Decision Support Systems: An Organizational Perspective, Addison-Wesley, Reading, MA, 1978.
[38] S. Kirkpatrick, Optimization by simulated annealing: quantitative studies, Journal of Statistical Physics (1984) 975–986.
[39] S. Kirkpatrick, C.D. Gelatt Jr., M.P. Veechi, Optimization by simulated annealing, Science 220 (1983) 671–674.
[40] Y. Kodratoff, R.S. Michalski, Machine Learning: An Artificial

Intelligence Approach, vol. 3, Morgan Kaufmann, San Mateo, CA, 1990.
[41] M.J. Kuchinski, Battle Management Systems Control Rule Optimization Using Artificial Intelligence, Technical Report No. NSWC MP 84-329 (Naval Surface Weapons Center, Dahlgren, VA, 1985).
[42] T. Liang, B.R. Konsynski, Modeling by analogy: use of analogical reasoning in model management systems, Proceedings of the 1990 ISDSS Conference, 1990, pp. 405–421.
[43] C. Lindblom, The Intelligence of Democracy, Free Press, New York, 1965.
[44] C. Lindblom, The science of muddling through, Public Administration Review 19 (1959) 79–88.
[45] M.L. Manheim, Issues in design of a symbiotic DSS, Proceedings of the 22nd Hawaii International Conference on System Sciences, vol. 3 (1989) 14–23.
[46] G.M. Marakas, Decision Support Systems in the Twenty-first Century, Prentice-Hall, New Jersey, 1999.
[47] N. Metropolis, A. Rosenbluth, M. Rosenbluth, A. Teller, E. Teller, Annealing: an algorithm, Journal of Chemistry and Physics 21 (1953) 1087–2006.
[48] R.S. Michalski, Understanding the nature of learning, in: R.S. Michalski, J.G. Carbonell, T.M. Mitchell (Eds.), Machine Learning: An Artificial Intelligence Approach, vol. 2, Morgan Kaufmann, San Mateo, CA, 1986.
[49] R.S. Michalski, Y. Kodratoff, Research in machine learning: recent progress, classification of methods and future directions, in: R.S. Michalski, J.G. Carbonell, T.M. Mitchell (Eds.), Machine Learning: An Artificial Intelligence Approach, vol. 3, Morgan Kaufmann, San Mateo, CA, 1990.
[50] K.E. Moffitt, An Empirical Test of Expert System Explanation Facility Effect on Incidental Learning and Decision-Making, PhD Dissertation, Arizona State University, 1989.
[51] P. Ninios, K. Vlahos, D.W. Bunn, Industrial simulation: system modeling with an object oriented/DEVS technology, European Journal of Operations Research 81 (1995).
[52] P.C. Nystrom, W.H. Starbuck, To avoid organizational crises, unlearn, organizational dynamics, Spring, 1984, 53–65.
[53] R. Pakath, J.S. Zaveri, Specifying critical in a genetics-driven decision support system: an automated facility, Decision Sciences 26 (1995) 749–779.
[54] H.L. Poh, A neural network approach for decision support, International Journal of Applied Expert Systems 2 (1994).
[55] M.S. Poole, G. DeSanctis, Use of group decision support systems as an appropriation process, IEEE, 1989, pp. 141–157.
[56] C.K. Prahalad, G. Hamel, The core competence of corporation, Harvard Business Review 68 (1990) 79–93.
[57] P. Sange, The Fifth Discipline: The Art and Practice of Learning Organizations, Doubleday, New York, 1990.
[58] E.H. Schein, Innovative cultures and organizations, in: T.J. Allen, M.S. Scott-Morton (Eds.), Information Technology and Corporations of the 1990s, Oxford Univ. Press, New York, 1991.
[59] S. Schocken, G. Ariav, Neural networks for decision support: problems and opportunities, Decision Support Systems 11 (1994).
[60] J.W. Shavlik, T.G. Dietterich, Readings in Machine Learning, Morgan Kaufmann, San Mateo, CA, 1990.
[61] H.A. Simon, Why should machines learn? in: R.S. Michalski, J.G. Carbonell, T.M. Mitchell (Eds.), Machine Learning: An Artificial Intelligence Approach, vol. 1, Morgan Kaufmann, California, 1983, pp. 25–37.
[62] P.E. Taylor, S.J. Huxley, A break from tradition for the San Francisco police: patrol officer scheduling using an optimization-based decision support system, Interfaces 19 (1989) 4–24.
[63] E. Turban, J.E. Aronson, Decision Support Systems and Intelligent Systems, Prentice-Hall, New Jersey, 1998.
[64] J.P. Walsh, G.R. Ungson, Organizational memory, Academy of Management Review 16 (1995) 57–91.
[65] J. Wang, Artificial neural networks v/s natural neural networks, Decision Support Systems 11 (1994) 415–429.
[66] K. Weick, The Social Psychology of Organizations, 2nd edn., Addison-Wessley, Reading, MA, 1979.
[67] K. Weick, Sensemaking in Organization, Sage Publications, Thousand Oaks, CA, 1995.
[68] D. Whitley, T. Starkweather, D. Shaner, Traveling salesmen and sequence scheduling: quality solutions using genetic edge recombination, in: L. Davis (Ed.), Handbook of Genetic Algorithms, Van Nostrand-Reinhold, New York, 1990.
[69] R.B. Zmud, W. Anthony, R. Stair, The use of mental imagery to facilitate information identification in requirement analysis, Journal of Management Information Systems 9 (1993) 175–191.

Ganesh D. Bhatt is an Assistant Professor of Information Science and Systems at Morgan State University. He obtained his DBA from Southern Illinois University at Carbondale and MTech and BTech degrees from I.I.T. Delhi and I.T.B.H.U. Varansi (India), respectively. He has over 12 research publications that have appeared in ***OMEGA***, *International journal of Operation and Production Management*, *Journal of Knowledge Management*, *Journal of Knowledge and Process Management*, *Supply Chain Management*, and others. His current research interests are in knowledge management and e-commerce areas.

Dr. Jigish Zaveri is an Associate Professor in the Department of Information Science and Systems, Earl Graves School of Business and Management at Morgan State University. He holds PhD and MS degrees from University of Kentucky and a BTech degree from Indian Institute of Technology. Dr. Zaveri's research interests encompass ***Knowledge Management***, *Decision Support Systems*, *Artificial Intelligence*, and others. Dr. Zaveri has numerous research publications that have appeared in *Decision Support Systems*, *Decision Science*, and *IEEE Transactions on Systems, Man, and Cybernetics*, and a book chapter in *Manufacturing Decision Support Systems* (Chapman–Hall). He also has numerous research presentations and articles presented at major conferences and has worked on numerous projects for several agencies including the National Transportation Center (Systems Analysis), and the National Security Agency (Data Analysis).