Updated Architectures for the Integration of Decision Making Support Functionalities

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INTRODUCTION

Information systems research continues to examine ways to improve support for decision making. The evolution from simple data access and reporting to complex analytical, creative, and artificially intelligent support for decision making persists (Holsapple & Whinston, 1996). In the evolution, existing information systems still, and new intelligent systems have been created to, provide the desired decision making support.

By studying the existing, and new, systems' characteristics, advantages, and disadvantages, researchers and practitioners can better design, develop, and implement robust decision making support systems (Kumar, 1999). The original article facilitated such study by presenting and illustrating the underlying information system architectures for robust decision making support (Forgionne, 2005).

This article updates the original by offering additional contributions to the subject. New literature on intelligent decision making support is examined, and the relevant findings are discussed. The title has been modified slightly to reflect the updates.

BACKGROUND

Several frameworks have been developed to describe the human decision making process. The most popular is Simon's three-phase paradigm of intelligence, design, and choice (Simon, 1960). This paradigm seems to be the most general, implying virtually all other proposed frameworks, and the Simon paradigm appears to have best withstood empirical testing (Martinsons, Davison, & Tse, 1999). Such scrutiny, however, has suggested the expansion of the basic formulation to conclude with an implementation phase.

During the intelligence phase, the decision-maker observes reality, gains a fundamental understanding of existing problems or new opportunities, and acquires the general quantitative and qualitative information needed to address the problems or opportunities. In the design phase, the decision-maker develops a specific and precise model that can be used to systematically examine the discovered problem or opportunity. This model will consist of decision alternatives, uncontrollable events, criteria, and the symbolic or numerical relationships between these variables. Using the explicit models to logically evaluate the specified alternatives and to generate recommended actions constitute the ensuing choice phase. During the subsequent implementation phase, the decision maker ponders the analyses and recommendations, weighs the consequences, gains sufficient confidence in the decision, develops an implementation plan, secures needed financial, human, and material resources, and puts the plan into action.

A variety of individual information systems have been offered to support the decision-making phases and steps. Much can be learned about this support by examining the individual systems' components, architectures, and operations.

RENDERING EFFECTIVE DECISION MAKING SUPPORT

Issues, Controversies, and Problems

Decision making support has evolved over time and across disciplines (Mirchandani & Pakath, 1999). Initial support was offered by a decision support system (DSS). In the typical DSS, the decision maker utilizes computer technology to: (a) organize the data into problem parameters, (b) attach the parameters to a model, (c) use the model to simulate (experiment with) alternatives and events, and/or (d) find the best solution to the problem. Results are reported as parameter conditions (status reports), experimental forecasts, and/or recommended actions. Feedback from the user-controlled processing guides the decision maker to a problem solution, and created information and knowledge are stored as additional inputs for future or further processing.

The DSS concept presumes that the problem pertinent data and models have been created and stored in the system prior to use (Hooghiemstra, Kroon, Odijk, Salomon, & Zwaneveld, 1999). This concept also assumes that the user can utilize the computer technology to perform the technical processing operations and computations required by the system (Lawrence & Sim, 1999). In fact, DSS users rarely have the technical skill to recognize, capture, and process pertinent data and models or to interpret the results of the models' processing within the problem context (Raghunathan, 1999). In short, the DSS concept offers little direct support

for the intelligence, early design, and implementation phases of decision making.

To be useful, problem pertinent data must be identified, located, captured, stored, accessed, and interpreted (Seely & Targett, 1999). Data warehousing can facilitate access and reporting, while data mining can help with the interpretation function. An executive information system (EIS) can deliver these data access, reporting, and interpretation functions to the decision maker in an intuitive and appealing manner.

In a typical EIS, the decision maker utilizes computer technology to: (a) organize the data into specified broad categories, (b) view (slice and dice) the data from interesting perspectives, (c) generate "warnings" for the decision maker by scanning current trends, and (d) mine the data for less obvious relationships. Results are reported as category summaries (status reports), sliced and diced details (drill down reports), and/or suggested problem parameters (events). Feedback from the user-controlled processing guides the decision maker to a general problem understanding, and the created parameters are stored as additional inputs for further processing.

The user should exit EIS processing with a general understanding of the problem or opportunity and with relevant problem information (such as general objectives, range of decision alternatives, and range of pertinent events). Since additional decision analysis will be required to explicitly formulate the problem and complete the decision making process, an EIS directly supports only the intelligence phase of decision making.

Technical and domain expertise will be needed to recognize, formulate, and solve most complex and significant decision problems or opportunities. Although such expertise will be available within, and outside, an organization, the expertise may be difficult, costly, and time-consuming to locate, access, and utilize. Often, the corresponding knowledge can be acquired, embedded within a knowledge-based system (KBS), and the system can be used to capture, store, and deliver the expertise to the decision maker (Ayyub, 2001). A typical KBS captures and stores as inputs problem pertinent knowledge, either from experts, cases, or other sources, and the models (inference engine or reasoning mechanisms) needed to draw problem solution inferences from the knowledge. In the process, a KBS directly facilitates

problem structuring (thereby supporting part of the design phase), the selection of alternatives, and the evaluation of the selections (hence supporting the choice phase of decision making).

Since decision making is a sequential and continuous process, learning will be essential to the successful completion of the process. Users will learn from their interactions with a KBS (or other individual decision making support system) and, in the process, gain skills that can be applied to further decision making tasks. Applying learning to the solution of the current problem, however, often will require system support (Bolloju, Khalifa, & Turban, 2002). Machine-learning systems (MLS) can provide such support by mimicking the learning processes of physical systems. In a typical MLS, the decision maker utilizes computer technology to: (a) organize the problem data, (b) structure (operationalize) the learning model, and (c) simulate learning. Results are reported as problem conditions (status reports), forecasted problem outcomes, and/or and an explanation of the learning logic.

Besides learning, creativity often is needed to successfully complete the decision making process (Keys, 2000). While the previous systems free decision makers to concentrate on the creative aspects of decision making, they do not provide direct support for the creative process (Savransky, 2001). Since decision makers may not be inherently creative, support for creativity can considerably enhance their decision making. A creativity enhancing system (CES) offers such support (Forgionne, Clements, & Newman, 1995). In a typical CES, the decision maker utilizes computer technology to: (a) organize (chiefly categorize and classify) problem ideas and concepts, (b) structure ideas and concepts into problem elements and relationships, and (c) simulate conceptual problem solutions. Results are reported as problem elements (status reports), the problem's conceptual structure (criteria, alternatives, events, and relationships), and/or forecasted outcomes from the conceptual analyses.

The major individual systems, and their primary and direct support, are summarized in Table 1. An examination of this table shows that none of the individual systems offers complete and integrated support for all phases and steps of the decision making process.

Table 1. Individual decision making support systems

System	Type	Support
Decision Support System	Individual	Specifying relationships between criteria, alternatives, and events; choice
Executive Information System	Individual	Intelligence; developing decision criteria; identifying relevant uncontrollable events
Knowledge-Based System	Individual	Develop decision alternatives; choice
Machine-Learning System	Individual	Logically evaluate decision alternatives
Creativity Enhancing System	Individual	Design; develop an implementation plan; put implementation plan into action

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