The Evaluation of Decision-Making Support Systems' Functionality

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INTRODUCTION

Contemporary decision-making support systems (DMSSs) are large systems that vary in nature, combining functionality from two or more classically defined support systems, often blurring the lines of their definitions. For example, in practical implementations, it is rare to find a decision support system (DSS) without executive information system (EIS) capabilities or an expert system (ES) without a recommender system capability. *Decision-making support system* has become an umbrella term spanning a broad range of systems and functional support capabilities (Alter, 2004). Various information systems have been proposed to support the decision-making process. Among others, there are DSSs, ESs, and management support systems (MSSs). Studies have been conducted to evaluate the decision effectiveness of each proposed system (Brown, 2005; Jean-Charles & Frédéric, 2003; Kanungo, Sharma, & Jain, 2001; Rajiv & Sarv, 2004). Case studies, field studies, and laboratory experiments have been the evaluation vehicles of choice (Fjermestad & Hiltz, 2001; James, Ramakrishnan, & Kustim, 2002; Kaplan, 2000).

While for the most part each study has examined the decision effectiveness of an individual system, it has done so by examining the system as a whole using outcome- or user-related measures to quantify success and effectiveness (Etezadi-Amoli & Farhoomand, 1996; Holsapple & Sena, 2005; Jain, Ramamurthy, & Sundaram, 2006). When a study has included two or more systems, individual system effects typically have not been isolated. For example, Nemati, Steiger, Lyer, and Herschel (2002) presented an integrated system with both DSS and AI (artificial intelligence) functionality, but they did not explicitly test for the independent effects of the DSS and AI capabilities on the decision-making outcome and process. This article extends the previous work by examining the separate impacts of different DMSSs on decision effectiveness.

BACKGROUND

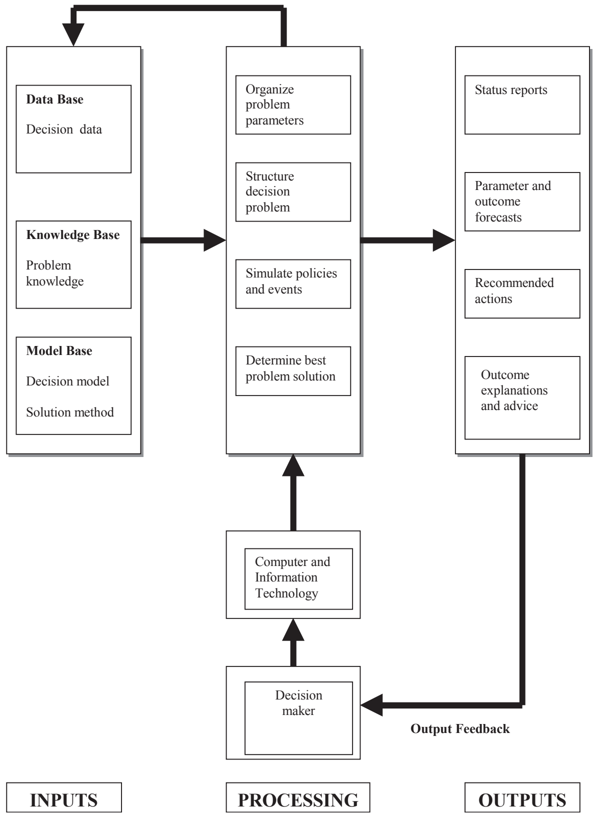
DMSSs are information systems that directly support the decision-making process for complex, high-level problems in an interactive manner (Alter, 2004; Mora, Forgionne, & Gupta, 2002). The specific DMSS can be a traditional DSS, EIS, ES, knowledge-based system (KBS), or a system that combines the functionalities of DSS, EIS, KBS/ES.

An architecture that incorporates the functionality of the various proposed systems is shown in Figure 1 (adapted from Forgionne, 2003).

In the typical DSS, the decision maker utilizes computer and information technology to (a) structure the problem by attaching the parameters to a model and (b) use the model to simulate (experiment with) alternatives and events and/or find the best solution to the problem (Borenstein, 1998; Raghunathan, 1999). Results are reported as parameter conditions (status reports), experimental outcome and parameter forecasts, and/or recommended actions. Feedback from user processing guides the decision maker to a problem solution, and created information is stored as an additional input for further processing. A DSS, then, would not include the knowledge base on the input side or offer explanations on the output side of Figure 1's conceptual architecture.

In a typical EIS, the decision maker utilizes computer and information technology to (a) access dispersed data, (b) organize the data into user-specified broad categories, (c) view the data from interesting perspectives, and (d) highlight important patterns by scanning current trends (Leidner & Elam, 1994; Seely & Targett,

Figure 1. General DMSS



1999). Results are reported as categorical summaries and drill-down details (status reports) and/or suggested problem parameters (parameter forecasts). Feedback from the user processing guides the decision maker to a general problem understanding, and the created parameters are stored as additional inputs for further processing. An EIS, then, would have a limited model base and not include the knowledge base on the input side. Additionally, the system would not offer recommended actions or explanations on the output side of Figure 1's conceptual architecture.

A typical KBS/ES 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 advice from the knowledge (O'Leary, 1998; Preece, 1990; Ullman, 1988; Waterman, 1985). Results are reported as knowledge summaries (status reports), forecasted outcomes, and/or problem advice and explanations for the advice. Feedback from the user processing guides the decision maker to the advice, and the created events and advice pathways are stored as additional inputs for further processing. A KBS/ES, then, would have a limited model base and not include the database on the input side, and similar to an EIS, the system would not offer recommendations on the output side of Figure 1's conceptual architecture.

An MSS integrates the functions of a DSS, EIS, and KBS/ES into a single system (Turban, Aronson, & Liang, 2004). Similar to its component systems, an MSS will have a model base and a database. The database contains data relevant to the decision problem, including the values for the uncontrollable events, decision alternatives, and decision criteria. The knowledge base holds problem knowledge, such as guidance for selecting decision alternatives and uncontrollable inputs, problem relationships, or advice in interpreting possible outcomes. The model base is a repository for the formal models of the decision problem and the methodology for developing results (simulations and solutions) using these formal models. Processing will generate status reports on events and alternatives,

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