# Evaluation of Decision-Making Support Systems

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## INTRODUCTION

Decision support systems (DSSs) have been researched extensively over the years with the purpose of aiding the decision maker (DM) in an increasingly complex and rapidly changing environment (Sprague & Watson, 1996; Turban & Aronson, 1998). Newer intelligent systems, enabled by the advent of the Internet combined with artificial-intelligence (AI) techniques, have extended the reach of DSSs to assist with decisions in real time with multiple informaftion flows and dynamic data across geographical boundaries. All of these systems can be grouped under the broad classification of decision-making support systems (DMSS) and aim to improve human decision making. A DMSS in combination with the human DM can produce better decisions by, for example (Holsapple & Whinston, 1996), supplementing the DM's abilities; aiding one or more of Simon's (1997) phases of intelligence, design, and choice in decision making; facilitating problem solving; assisting with unstructured or semistructured problems (Keen & Scott Morton, 1978); providing expert guidance; and managing knowledge. Yet, the specific contribution of a DMSS toward improving decisions remains difficult to quantify.

Many researchers identify a single metric, or a series of single metrics, for evaluation of the DMSS in supporting decision making, if it is evaluated at all (Phillips-Wren, Mora, Forgionne, Garrido, & Gupta, 2006). The authors suggest outcome criteria such as decreased cost, or process criteria such as increased efficiency, to justify the DMSS. Yet no single integrated metric is proposed to determine the value of the DMSS to the decision maker.

The objective of this article is to review literature-based evaluation criteria and to provide a multicriteria evaluation model that determines the precise decision-making contributions of a DMSS. The model is implemented with the analytical hierarchy process (AHP), a formalized multicriteria method.

Building on other core studies (Forgionne, 1999; Forgionne & Kohli, 2000; Keen, 1981; Leidner & Elam, 1993; Money, Tromp, & Wegner, 1988; Phillips-Wren & Forgionne, 2002; Phillips-Wren, Hahn, & Forgionne, 2004; Phillips-Wren, Mora, Forgionne, Garrido, et al., 2006; Phillips-Wren, Mora, Forgionne, & Gupta, 2006; Pieptea & Anderson, 1987), this article focuses on the performance and evaluation of a planned or real DMSS in supporting decision making. Unlike previous DSS studies (Sanders & Courtney, 1985; Leidner, 1996; Wixom & Watson, 2001; Mora, Cervantes, Gelman, Forgionne, Mejia, & Weitzenfeld, 2002) or general information-system studies (DeLone & McLean, 1992, 2003), this study develops a DMSS evaluation model from a design research paradigm, that is, to be built and evaluated (Hevner & March, 2003).

## BACKGROUND

Although developers of DMSSs generally report a single criterion for a DMSS, the use of multiple criteria to evaluate a DMSS has been reported in the literature. Chandler (1982) noted that information systems create a relationship between users and the system itself, so that its evaluation should consider both user and system constraints. He developed a multiple-goal programming approach to consider trade-offs between goals and performance. Adelman (1992) proposed a comprehensive evaluation for assessing specifically DSSs and expert systems using subjective, technical, and empirical methods to form a multifaceted approach. User and sponsor perspectives were included in the subjective methods. The analytical methods and correctness of the analysis were assessed in the technical evaluation. Finally, a comparison of performance with and without the system was evaluated in the empirical-methods section. The three approaches were combined to form an overall evaluation of the system. Turban and Aronson (1998) indicate that information systems, including DMSSs, should be evaluated with two major classes of performance measurement: effectiveness and efficiency. According to general systems principles (Checkland, 1999), effectiveness deals with how well the results or outputs contribute to the goals and achievements of the wider system, and efficiency measures how well the system processes inputs and resources to achieve outputs. A third measure, efficacy, deals with how well the system produces the expected outputs. This third measure complements the three general performance or value-based measures for any general system. For example, Maynard, Burstein, and Arnott (2001) proposed evaluating DMSSs by directly including the perspectives of different constituencies or stakeholders in a multicriteria evaluation.

## DECISION VALUE OF DMSS

### Multicriteria Model

Of the many studies of applied DMSSs published in the last 30 years, assessment usually consisted of characteristics associated with either the process or outcome of decision making using a DMSS (Forgionne, 1999; Phillips-Wren, Mora, Forgionne, Garrido, et al., 2006; Phillips-Wren, Mora, Forgionne, & Gupta, 2006). Process variables assess the improvement in the way that decisions are made and are often measured in qualitative terms. Process variables that have been used to judge a DMSS are increased efficiency, user satisfaction, time savings, more systematic processes, better understanding of the problem, and ability to generalize. Outcome variables assess the improvement in the decision quality when the DM uses the DMSS for a specific decision and are often measured in quantifiable terms. Outcome variables in the literature are, for example, increased profit, decreased cost, accuracy of predicting annual returns, and success in predicting failures.

These two categories of outcome and process are classical descriptions of decision making. Simon (1997) characterized decision making as consisting of the phases of intelligence, design, and choice. The intelligence phase concerns the identification of the problem and data collection, design includes the formulation of the model and search for alternatives, and choice includes the selection of the best alternative. Once the decision is made, the outcome of the decision can be evaluated. Since DMSSs affect both process and outcome, particularly in real-time systems, DMSSs should be evaluated on both criteria.

Previous research (Forgionne, 1999; Phillips-Wren & Forgionne, 2002; Phillips-Wren et al., 2004) has shown that a multicriteria model for the evaluation of DMSSs can be developed based on criteria in the literature. Although other authors have addressed multiple dimensions for information systems success in general (DeLone & McLean, 1992, 2003) and multiple factors for DSS evaluation in particular (Maynard et al., 2001; Sanders & Courtney, 1985), our proposed evaluation model focuses on how well the DMSS supports the specific decision for which it is intended. Our position is that the decision value of a DMSS should be evaluated based on its support for both the process and outcome of decision making. The decision value of the system can be determined quantitatively using a multiple-criteria model such as the AHP with the additional advantage that the precise contributions of the system to the subcomponents in the model can be determined. A stochastic enhancement of the AHP allows the determination of the statistical significance of the contributions (Phillips-Wren et al., 2004).

The AHP (Saaty, 1977) is a multicriteria model that provides a methodology for comparing alternatives by structuring criteria into a hierarchy, providing for pairwise comparisons of criteria at the lowest level of the hierarchy to be entered by the user, and synthesizing the results into a single numerical value. For example, the decision value of alternative DMSSs can be compared based on criteria and subcriteria. The AHP has been extensively used in decision making for applied problems (Saaty & Vargas, 1994). Once the hierarchy is established, the alternatives are evaluated by pairs with respect to the criteria on the next level. The criteria can be weighted, if desired, according to the priority of each criterion. An eigenvalue solution is utilized to

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