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The Use of Simulation as an Experimental Methodology for DMSS Research

Guissepi Forgionne
University of Maryland, Baltimore County, USA

Stephen Russell
University of Maryland, Baltimore County, USA

INTRODUCTION

Decision-making support-system (DMSS) research has been based largely on case and field studies of real organizations or entities and laboratory experiments involving human participants. Each methodology has provided useful results. Case and field studies can identify and describe relevant variables and relationships, suggest theories, and offer conceptual and practical models for evaluation (Benbasat, Goldstein, & Mead, 1987; Fjermestad & Hiltz, 2000; Orlikowski & Baroudi, 1991). Participant-based laboratory experiments can provide initial theory and model hypothesis tests, identify key evaluation assumptions, and offer suggestions for future research (Amaratunga, Baldry, Sarshar, & Newton, 2002; Das, 1983; Patton, 2002).

Case and field studies and participant-based laboratory experiments, however, have limitations for decision-making support evaluation. In each setting, it is difficult to acquire and motivate the participants. Real organizations and entities are reluctant to disrupt operations or provide proprietary information. Laboratory participants often consist of students in university-based studies, and as such frequently have little actual knowledge of the decision situation or incentive to mimic real behavior. Even decision-knowledgeable participants may, for political, psychological, or other reasons, mask real behavior.

In addition, case studies, field trials, and laboratory settings may not be representative of the population. By their nature, case and field studies usually involve few organizations or entities. Given the diversity experienced in practice, the few organizations or entities, even if selected judiciously, are unlikely to capture the disparity. While great care may be exercised in selecting sample participants for laboratory experiments, there will be Type I and Type II errors that result from even well-designed experiments (Alavi & Joachimsthaler, 1992).

As an alternative, simulation can be used to gather pertinent data and test corresponding hypotheses. Since an extremely large number of trials can be performed in a very short period of time, simulation is much more efficient and cost effective than case studies, field studies, or laboratory experiments (Balci, 1989; Evan & Olson, 2002; Tekin & Sabuncouglu, 2004). Also, the entire population can be simulated rather than a sample of objects or participants. Hence, simulation is more likely than the alternatives to produce generalizable results (David & Barry, 2001; McLeod, 1986; Yi, Lilja, & Hawkins, 2003a).

To utilize simulation appropriately in decision-making support evaluation, the application should involve a realistic high-level and complex problem faced by diverse decision makers in disparate organizations (Adleman, 1991; Turban, Aronson, & Liang, 2004). In addition, the problem must be capable of expression as a formal and explicit model with well-defined variables and relationships (Amigo, Puente, & Gregorio, 2004; Yi, Lilja, & Hawkins, 2003b). The variables can be measured, and the relationships expressed, qualitatively or quantitatively (Balci, 1994; Jeffrey, 1990; Murray, 2006). Data must be available to operationalize the model in disparate applications (Chakravorty & Franza, 2005; Stigall & Huggahalli, 1991).

The typical methodology is to develop a model (usually mathematical in form) of the problem and then use the model to experiment with variables using data generated empirically, theoretically, and by a combination of these methods (Greenwood et al., 2005). Such a methodology is used in this study to gather data for, and test hypotheses involving, DMSS.

The methodology is demonstrated by comparing the effectiveness of alternative decision-making support systems. The article describes the problem, explains the methodology, and then illustrates the application. We close with conclusions and implications for information systems research.

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BACKGROUND

There are several concepts underlying simulation. These include the system and model, system state variables, entities and attributes, list processing, activities and delays, and the definition of discrete-event simulation (Banks, 1998). Essentially, simulation is a technique for conducting experiments. First, a model is built that accurately imitates reality. The process starts with an explicit and precise definition of the performance measures, key events, controllable actions, and decision objective (or objectives). Then, by experimenting with the model, the researcher can study the characteristics and behavior of the real situation.

Pritsker (1989) states,

Simulation works because we abstract reality and because we, as problem solvers, are realistic modelers and analysts. We combine the engineering concepts of design and control with the experimental approach of the scientist. We use mathematics to solve problems and verify solutions. The ability to resolve problems involving choice requires the involvement of a decision maker. We have a difficult time modeling the decision maker, so we mimic the decision-making process and provide information to that used in actual operations, that is, in practice.

The challenges of evaluating decision-making support systems, particularly systems with complicated outputs such as critiques or graphical reports as opposed to simpler decision support systems (DSSs; i.e., a reminder system), remains a contemporary and relevant research issue (Potts, Wyatt, & Altman, 2001). A common approach to DMSS evaluation is through the use of clinical, case, or field trials using human decision makers. The use of laboratory participants can be a very effective methodology for validating a decision support system, but may have limitations in verifying the system. Sojda (2004) cites several works noting the distinction between validation and verification. O'Keefe, Balci, and Smith (1987) and Boehm (1981) define the distinction as "validation means building the right system. Verification means building the system right." In this context, simulation can provide a broad generalizable methodology for the evaluation of decision-making support systems.

STRATEGY SIMULATION FOR HYPOTHESIS TESTING

In a wide variety of organizations, various top-level managers must develop strategic plans that involve a complex combination of marketing, production, and financial activities (Paul, 2005; Sutton & Michael, 2006; Teece, Pisano, & Shuen, 1997). The plans should consider environmental variables, such as competition, general economic conditions, seasonal fluctuations, and other factors. Since the environmental factors and the relationships between these variables, the organizational activities, and the decision objectives are only partially understood, this strategic planning problem is semistructured. This semistructure, the complexity of the problem, and the need for top-management input make the problem a suitable candidate for decision-making support (Eisenhardt & Zbaracki, n.d.; Elbanna & Said, 2006).

There are many models of strategic planning available (Fuglseth & Gronhaug, 2003; Palanisamy, 2005; Wernerfelt, 1990). One typical model expresses the essential characteristics and relationships involved in strategic planning as a series of equations. Because the equations are realistic and comprehensive, this typical model has been used to train and evaluate disparate management personnel in a wide variety of organizations. In the model equations, the variables and relationships are well defined and explicit, and data ranges are established for the variables. Consequently, this typical model is a good candidate to illustrate the simulation approach to DMSS evaluation.

Management Problem

The problem involves a market in which an organization competes for a product's four-quarter total market potential based on price, marketing, and other factors. Demand for the organization's products will be influenced by (a) the firm's actions, (b) the competitors' behavior, and (c) the economic environment (McLeod, 1986).

In this decision environment, top-level management must plan a four-quarter strategy that would generate as much total profit as possible. Strategy making requires (a) setting the levels of four decision variables (the product price, marketing budget, research and development expenditures, and plant investment) and (b) forecasting the levels of four key uncontrollable variables (the

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