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Abstract

There is a need to develop a better understanding of decision making -- how humans learn, create, receive, store, and process information; and the role that computers play in enhancing this process. The potential of decision aids to bridge the gap has not been realized. The goal is to improve decision outcomes and to enhance the decision-making process. This research is concerned with investigating the decision-makers' ability to discover, collect, represent, transmit, and apply information, thereby improving the way simulation models are developed (efficiency) which will result in better outcomes (effectiveness).

Keywords: Empirical, guidance, rule-base, simulation, queue

Introduction

The technological explosion of the Internet in the late 1980s and early 1990s has resulted in a paradigm shift that has affected all aspects of our lives. These technologies have enhanced the connectivity between people to people, to powerful databases, to computing tools, and to institutions around the globe. This connectivity is enabling more people to become knowledge workers, and it has helped produce advanced developments in many areas but especially in the organizational information system arena. Research in information systems has been driven by these technological trends. This paradigm has had a profound effect on IS research. Among the very complex processes that are necessary to the development, design and operation of advanced technological systems, the human decision making process may very well be the weakest link. In many of today's complex environmental situations, problems can seem to be beyond the scope of known strategies, and resources needed, for solving them. The interactive knowledge-based approach can be used to support the decision-making process (Leonard-Barton & Sviokla, 1988; Sviokla, 1990; Dhar & Stein, 1997). This paper proposes to develop "intelligence" (a reasoning mechanism) in a system that can guide, and interact with, the human user to solve problems. This paper focuses on one such area: the development of an intelligent DSS through an interactive approach to aid decision-makers in formulating simulation models to address real-world problems. There is a need to develop a better understanding of decision making -- how humans learn, create, receive, store, and process information; and the role that computers play in enhancing this process. The goal is to improve decision outcomes and to enhance the decision-making process. This research will involve evaluating the decisional guidance aspect of the intelligent DSS in relation to its impact on the decision-making process(efficiency) and outcomes(effectiveness).

Approach

Decision-making involves making primary and secondary decisions (Remus and Kottemann, 86; Silver, 1990; Silver, 1991). Primary decisions are the decision-making and secondary decisions are deciding how to decide. Decisional guidance supports secondary decisions. Secondary decisions have a major impact on the decision-making process and can often be influenced by individual biases. Decisional guidance can be utilized to overcome the user's biases, if any. (Silver, 1991) defined "decisional guidance" as follows:

> Decisional Guidance: how a decision support system enlightens or sways its users as they structure and execute their decision-making processes - that is, as they choose among and use the system's functional capabilities.

Decisional guidance can be used to restrict (Silver, 1988) the solution space so as to increase the decision-making efficiency and also overcome the biases that decision-makers can have. (Remus and Kottemann, 1986) discussed some of the types of biases at length in their paper. Biases can influence the decision-maker's perception of a problem, which in turn affects the decision-making process. Decisional guidance in a DSS can assist or direct decision-makers in the decision-making process through directed or non-directed means (Silver, 1990). It had been stated (Brown, 2000) that:

> Decision-making needs improvement. The potential of decision aids to bridge the gap has not been realized. The aiding art is still primitive. Little research is being done that could further the art, because researchers are motivated to do what is scientifically attractive, rather than useful.

This research is an attempt to bridge "the gap." In particular, this research is concerned with evaluating the role of decisional guidance in improving the decision-makers' ability to discover, collect, represent, transmit, and apply information, thereby improving the way simulation models are developed (efficiency) which will result in better outcomes (effectiveness).

In practice, problems often are complex and not well structured. Problem solving is often a multi-step process that uses knowledge to determine the best approach and to formulate model/s that can be used to derive solution/s. There are often different approaches and different types of models that can be formulated to solve a problem. The knowledge-based approach can be used to increase the efficiency of the decision making process and improve the decision outcomes. Encoding knowledge into rules is the most common form of knowledge representation for knowledge-based systems (KBS) (Gonzalez and Dankel, 1993). The rule-base is invoked by presenting the KBS with a specific problem description or case, and by the KBS searching through its knowledge of rules and facts for an answer. The mechanism used to draw conclusions based on rules in the knowledge base and the data for the current case is the KBS's reasoning process or inference strategy. The inference engine can be used to establish the context (to provide guidance) for each step in the decision-making process. Many real world problems are ill-structured or "wicked." One purpose of an intelligent DSS is to promote learning so that a problem structure can be created to systematically evaluate possible alternative solutions. It might not be possible to obtain an optimal solution but often a good solution that is feasible can be obtained. This approach is applied to a real semi-structured problem - a queuing problem at a metropolitan bus depot. This case can be solved using simulation. A model of a single queue, multi-server queuing system is to be built and simulated. The result is then compared with, and verified by, the queuing theory recommendations. The goal is to develop a simulation model of a single queue, multi-server queuing system of a bus depot which is able to reproduce the effects or conditions of the existing system, as well as be able to model the effect of changes in system components so as to improve the efficiency of the system. As space is a critical factor at the bus terminal we want to limit the maximum queue length and with minimum cost. The intelligent DSS (iDSS), a KBS system, will provide informational guidance while a base DSS will provide only suggestive guidance (Silver, 1991). The results from the two systems as applied to the case will then be compared. The research questions are:

1. Can the iDSS (informational guidance) improve decision-making outcomes relative to the DSS (suggestive guidance)?
2. Can the iDSS (informational guidance) improve the decision-making process relative to the DSS (suggestive guidance)?

Methodology

Student subjects were solicited from upper division information systems classes. As an incentive, students will be awarded points (up to a maximum of 10%) based on their solutions towards their final score for the classes. The experiments will be conducted during laboratory sessions, which are part of the regular classes. The experiment is adapted from schemes that had been used in previous successful studies (Elam & Mead,1990; Adelman, 1991; Gardner et. Al., 1993; Creswell, 1994; Kohli & Forgionne, 2000). Subjects were trained in simulation and queuing theory, and in the use of computer-based DSS until they were all able to solve the exercises that were assigned to them. The experiment proper will start off with a new case (metropolitan bus service) which is similar but not the same as the exercises that the subjects had worked on. The subjects will be randomly divided into two groups for a within-subjects evaluation. One group will start with the iDSS while the other group will start with the DSS. The subjects will be allowed to run as many trials as desired in a 45 minutes session to obtain the best solution. The within-subject design has been shown to be beneficial for subject heterogeneity (Keppel, 1982; Maxwell & Delaney, 1990; Kohli & Forgionne, 2000). There will be a lapse of two weeks between treatments so as to dissipate any learning by the subjects about the experimental case. At that time, previous iDSS users will be given the base DSS, and vice versa.

At the start of the experiment, the subjects will be given a questionnaire to collect data on the subjects' demographics and experience level. At the end of the experiment, the subjects will fill another questionnaire to record the time taken and number of alternatives considered, print the results of the simulation and also rate on a 5-point Likert scale the least helpful to most helpful of the guidance provided at each decision making of both systems. The decision-making step components will be verified (with Cronbach's α by an item analysis to verify that the questionnaire reliably measures the subjects' decision making process self-ratings.

Discussion

From the first questionnaire, the collected demographic data will be categorical (non-metric) and the experience levels are ordinal (non-metric). The results of the simulation will be metric in nature. The decision-making process data can be treated as interval-scaled and therefore as metric. Non-metric data will be summarized with cross-tabulations and frequency distributions, while the metric data will be summarized with measures of central tendency and dispersions. Multivariate analysis will be used to test the hypothesis that the outcome and the process measures were each independent of the study group. Since the outcomes and the process ratings are metric, MANOVA will be used to statistically test the hypotheses.

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