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The effect of human pattern-recognition abilities in improving DSS performance

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ABSTRACT

In this paper, the function of a data-centred decision-support system (DSS) is simulated to investigate whether the incorporation of human pattern-recognition abilities significantly improves the performance of a system. Two decision making scenarios are considered. In one scenario, there is no human interaction, whereas the other scenario uses the pattern-recognition capabilities of humans. The simulation is performed by mining 10,000 records in 980 replications. The DSS has the ability to take corrective actions with the purpose of keeping the incoming data records within a given set of upper and lower boundaries. The results indicate that incorporating pattern-recognition ability in a DSS significantly improves the system's performance. However, the impact of human input is not linear with respect to system performance. Our study shows that a moderate degree of human intervention will usually provide the greatest positive impact on the system's performance.

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1. Introduction

A decision-support system is an 'alliance' between a decision maker and specialized support provided by information technology (IT). In this alliance, IT provides the capability of rapidly processing large amounts of data, whereas the decision maker provides capabilities in qualitative analysis and 'know-how' in the form of experience, intuition, judgment, and knowledge of relevant factors (Haag, Cumming, & McCubbrey, 2005; Hoch & Schkade, 1996).

There have been many efforts to 'close the gap' between human and machine, and thus optimize DSS performance. Dolk and Kridel (1991) proposed an active DSS in which computer and user worked as partners in the problem-solving process. Chuang and Yadav (1998) proposed a conceptual model which included a meta-level controlling unit that was capable of introspecting the system's capabilities and limitations, and determining appropriate actions to adjust the capabilities of the DSS. In a more recent study, Vahidov and Kersten (2004) advocated the development of a higher degree of effective interaction and proposed a new paradigm for computer-based decision support. In all of these studies, the essential issue is how the quality and flexibility of interaction between humans and computers can be improved (Beynon, Rasmequan, & Russ, 2002).

Over the years, research and practice have focused on developing DSSs that can use their processing power to compensate for the inherent weaknesses of the decision maker in data-centred and model-centred DSSs. This has usually been done by incorporating artificial intelligence techniques that mimic human behaviour (Keen, 1987; Liang, 1993; Radermacher, 1994), and by the development of 'adaptive' and 'evolutionary' support systems (Arnott, 2004).

The development of data warehouses that are capable of storing terabytes of data has facilitated the role of data-centred DSSs in supporting organizational decision making processes (Gray, 2006). In particular, organizations require information systems that are capable of analyzing and using information collected about customers or online visitors (Schonberg, Hoch, Podlaseck, & Spraragen, 2000). The key to the optimal use of these huge data warehouses are so-called 'data miners'. In most modern data-mining DSSs, the system takes inputs from users, uses these data to find patterns or to discover knowledge, and then supplies answers to users. In these circumstances, although the computer's processing power is fully utilized by data-mining algorithms, the user is only an observer and not an active participant in the discovery process. The strength of DSS in these cases depends on the capabilities of the DSS designers in making the DSS as comprehensive as possible.

Yet, it is known that human decision makers are better than machines at identifying relevant variables (Dawes, 1979). It is also known that pattern recognition is one of the fundamental capacities of human cognition (Andersen, 1983). In the quest for better interaction between humans and DSSs, several 'user-adaptive' models have been developed (Sankar et al., 1995).

Previous research recognizes that decision makers play a significant role in the performance of a DSS. Research also suggests that qualitative analysis performed by humans should be combined

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with the ability of the computers to process large amounts of data. Several models are suggested in the literature; however, there is a void in the body of literature with respect to the study and investigation of the degree of human–machine interaction. The premise of the present paper is that the performance of a decision-support system can be significantly facilitated if the decision maker is able to interact with the system and provide qualitative input as needed. This paper contributes to the existing body of literature by investigating different degrees of human–machine interaction within a DSS, and finding the ideal combination of the decision maker's capacity for *pattern recognition* and the computer's *processing power* that leads to the effective performance of the DSS.

The study simulates two decision making scenarios. Each scenario consists of a stream of data being monitored by a DSS. These data could reflect various parameters – such as consecutive online transactions, average customer spending over time, daily demand for a given product, and so on. The purpose of the DSS is to monitor these data, look for patterns, and ensure that the trend of incoming data remains within given boundaries. An example of such a system is the statistical control process, which is a process used to monitor standards, take measurements and corrective actions as a given product or service is being produced (Heizer & Render, 2004).

The difference between the two scenarios considered here lies in the different degrees of human interaction involved. The *first scenario* has no human interaction – that is, the DSS is based solely on its processing power to maintain the incoming data within the desired boundaries. Although no pattern recognition is simulated in this scenario, the computer is programmed to make a correction every time a sample of data is not within the given boundaries. The *second scenario* is similar to the first scenario in many respects, but adds another layer to the decision making process by incorporating the decision maker's ability to recognize unacceptable patterns and to indicate an appropriate correction. The two scenarios thus serve as microcosms of human–machine interaction under various degrees of variability and system tolerance in a data-centred DSS.

2. Decision making problems

2.1. Scenario 1

This scenario simulates the functions of a DSS that is designed to monitor and maintain randomly generated data within given boundaries. Fig. 1 illustrates the simulation model of such a scenario. This model has no 'human' ability to recognize patterns – that is, there is no interaction with a human decision maker and no automatic pattern-recognition capabilities.

The model first generates its initial parameters (such as the number of transactions to be monitored, sample size, and the value of pre-established boundaries); then the initial transaction value is randomly generated. In the experiment, different degrees of input variability are provided by changing the standard deviation of the input variable. In a normalized distribution, the experiment considers low variation (standard deviation = 1), normal variation (standard deviation = 2), and high variation (standard deviation = 3). The record value (x) of the sample distribution is calculated as follows:

$$x_i = N(x_{i-1}, \sigma) \quad \text{and} \quad x_0 = N(0, \sigma) \tag{1}$$

where x_i is the value for record i and $N_{x,\sigma}$ represents normal distribution with mean x and standard deviation σ (sigma).

Once a value is generated, it is checked to ascertain whether it falls within the pre-established boundaries. If it falls within the boundaries, the generated value is added to the observations of a defined sample of size n and the sample mean is then calculated by the processing power of the DSS. If it does not fall within the boundaries, the number of records out-of-bounds (ROB), which serves as the dependent variable, is increased; the value is still used to calculate the mean of the upcoming sample size.

The next step in the model is to compare the sample mean with the same pre-established boundaries. If the sample mean falls outside the pre-established boundaries, the DSS takes corrective action and makes the necessary adjustments. As indicated by formula (1), the adjustment process consists of allowing the next value to be based on the target value (in this case 0), rather than the allowing it to be based on the previous value (x_{i-1}). If the sample mean falls within the boundaries, no action is required. This process continues until the model reaches the number of transactions to be processed.

Assuming that the machine has the processing capability to process all transaction values, a smaller sample size means that a greater number of interactions is needed by the DSS to ascertain whether the sample mean value is falling within the boundaries. Sample size, thus, serves as the independent variable in the model. Indirectly, this variable represents the degree of interaction between the DSS and the system. It is postulated that a strong relationship exists between the independent variable (sample size or degree of interaction) and the dependent variable (ROB). Any such relationship will be tested for different levels of system tolerance.

Different degrees of tolerance can be simulated by changing the pre-established boundaries (also known as upper and lower control limits). A low level of tolerance will have the upper and lower control limits based on a 2-sigma tolerance for normal distribution (allowing 4.55% of samples to fall outside by chance), whereas a high level of tolerance will have the limits set for 3-sigma (allowing only 0.3% of the samples to fall outside the limits by chance). In general, it is postulated that a less-tolerant system will require a higher degree of interaction. In such systems, the decision maker needs to be in control and monitor the system more closely.

2.2. Scenario 2

In the second scenario, the system is able to recognize patterns – usually associated with the decision maker. Fig. 2 illustrates the structure of the simulation model of such a scenario.

In this scenario, although the DSS automatically makes the necessary corrections to keep the data within the defined boundaries, the human decision maker also observes the system for any pattern in data that can cause problems for the future behaviour of the system. As shown in Fig. 3, in this specific problem, the decision maker can recognize and take corrective actions for: (i) 'in control'; (ii) 'out of control'; (iii) 'upward trend'; or (iv) 'downward trend.' The decision maker takes corrective action as soon as a trend is identified.

Pattern recognition is directly related to the degree of interaction between the decision maker and the DSS. The degree of interaction is represented by the number of consecutive samples whose attribute is constantly increasing (six in Fig. 3c), or decreasing (eight in Fig. 3d). The degree of interaction is represented by m, the number of samples between sample 4 and k, assuming that samples in between have consecutively increasing values. Smaller values of m relate to a greater number of corrective actions by the decision maker. In the simulation model presented here, $m = 3$ represents a high degree of involvement, $m = 5$ represents a medium degree of involvement, and $m = 7$ represents a low degree of involvement.

The degree of human interaction, m, serves as an independent variable in this scenario. For the same machine-processing capability, it is postulated that there is a relationship between the inde-

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