SYSTEM DYNAMICS BASED LEARNING ENVIRONMENTS: A TECHNOLOGY FOR DECISION SUPPORT AND ASSESSMENT

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Traditionally decision support systems (DSS) are designed to help the users make better decisions. However, the empirical evidence concerning the impact of DSS on improved decision making and leaning in dynamic tasks is equivocal at best. In this article, we introduce a new type of DSS based system dynamics technology as tool not only to support users' decision making and leaning but can also provide an effective assessment of the performance and learning as well.

Introduction

Managers face problems that are increasingly complex and dynamic. Decision support system (DSS) are designed to assist them make better decisions. However, the empirical evidence concerning the impact of DSS on improved decision making and learning in dynamic tasks is equivocal at best (Klabbers, 2003; Todd and Benbasat, 1999; Sharda et al., 1988; Sterman, 2000). Over four decades of dynamic decision making studies have resulted in a general conclusion on why people perform poorly in dynamic tasks. In dynamic tasks, where a number of decisions are required rather than a single decision, decisions are interdependent, and the decision making environment changes as a result of the decisions or autonomously or both (Edwards 1962), most often the poor performance is attributed to subjects' misperceptions of feedback. That is, people perform poorly because they ignore time delays between their 'actions and the consequences' (Sterman, 2000) and are insensitive to the feedback structure of the task system (Diehl and Sterman 1995). Decision maker's mental models about the task are often inadequate and flawed (Kerstholt and Raaijmakers, 1997; Romme, 2004). In this paper we argue that system dynamics based interactive learning environments (ILEs) could provide effective decision support for dynamic tasks by reducing the misperceptions of feedback. How do we know that learning has occurred? We argue that the design of ILEs facilitate the automatic capture of decision making data and provides an effective learning assessment.

Background

Dynamic Decision Making

Dynamic decision-making situations differ from those traditionally studied in static decision theory in at least three ways: a number of decisions are required rather than a single decision, decisions are interdependent, and the environment changes, either as a result of decisions made or independently of them or both (Edwards, 1962). Recent research in system dynamics has characterized such tasks by feedback processes, time delays, and non-linearities in the relationships between decision task variables (Romme, 2004). Driving a car, managing a firm, and controlling money supply are all dynamic tasks (Diehl & Sterman, 1995) In these tasks, contrary to static tasks such as lottery type gambling, locating a park on a city map, and counting money, multiple and interactive decisions are made over several periods whereby these decisions change the environment, giving rise to new information and leading to new decisions (Forrester, 1961; Sterman, 2000).

ILE

We use “ILEs” as a term sufficiently general to include microworlds, management flight simulators, DSS, learning laboratories, and any other computer simulation-based environment – the domain of these terms is all forms of action whose general goal is the facilitation of dynamic decision making. Based the on-going work in the system dynamics discipline (Moxnes, 2004; Otto & Struben, 2004; Qudrat-Ullah, 2005b; Sterman, 2002), this conception of ILE embodies learning as the main purpose of an ILE. Under this definition of ILE, learning goals are made explicit to the decision-makers. A computer-simulation model is built to represent adequately the domain or issue under study with which the decision makers can experience and induce real world-like responses (Qudrat-Ullah, 2005a). Human intervention refers to active keying in of the decisions by the decision makers into the computer-simulation model via the interface of an ILE.

Performance in Dynamic Tasks

How well do people perform in dynamic tasks? The empirical evidence (Diehl & Sterman, 2000; Klabbers, 2003; Moxnes, 2004; Sterman, 2000) suggests almost a categorical answer: “very poorly”. Very often the poor performance in dynamic tasks is attributed to subjects’ misperceptions of feedback (Moxnes, 2004; Sterman, 2000). The misperception of feedback (MOF) perspective concludes that subjects perform poorly because they ignore time delays and are insensitive to feedback structure of the task system. The paramount question remains; are people inherently incapable of controlling system with time lags, non-linearities, and feedback loops? Contrary to Sterman’s MOF hypothesis, an objective scan of real world decisions would suggest that experts can deal efficiently with highly complex dynamic systems in real life, such as, for example, manoeuvring a ship through restricted waterways. The expertise of river pilots, for example, seems to consists more of using specific knowledge (e.g., pile moorings, buoys, leading lines) they have acquired over time than in being able to predict accurately a ship's movements (Schraagen, 1994). This example suggests that people are not inherently incapable of better performance in dynamic tasks. Instead, decision makers need to acquire the requisite expertise.

Decision Making and Learning Assessment with ILEs

There exist some fundamental barriers to developing expertise in dynamic tasks: (1) *dynamic complexity*: our limited ability to understand the impact of time delays between our actions and their consequences coupled with the interactions between feedback loops that are multiple and non-linear in character and are ever present in the task systems we face in the real world, (2) *information availability limitations*: information we estimate, receive, and communicate is often oversimplified, distorted, delayed, biased, and ambiguous, (3) *information processing limitations*: when it comes to decision making people generally adopt an event-based, open-loop view of causality, ignore feedback processes, fail to appreciate time delays and are insensitive to nonlinearities present in the feedback loop structures of the task system, perceive flawed cognitive maps of the causal structure of the systems, make erroneous inferences even about the simplest possible feedback systems, fall prey to judgmental errors and biases, defensive routines and implementation failure (Sterman, 2000). The effective DSS, therefore, should allow the users to overcome such impediments to decision making and learning in dynamic tasks.

ILEs meet this challenge through the provisions of (1) a representative simulation model of the task system, (2) powerful interface, and (3) human tutor support--the three fundamental components of any ILE.

Decision Support through the Simulation Model

The greatest strength and appeal of an ILE in supporting decision making and learning in dynamic tasks lies in its underlying simulation model. In an ILE, the simulation model is built on system dynamics methodology (Forrester, 1961). The fundamental premise of system dynamics methodology is that 'the structure of the system drives its behaviour'. That structure consists of feedback loops, stocks and flows, and nonlinearities arising from the interaction of these basic structures (Sterman, 2000; Oliva, 2003). A typical system dynamics model allows that:

- The interaction and feedback between the systems variables, over time, in and across various sectors (e.g., demand, supply, production, finances etc.) of the task system be explicitly represented and the structural assumptions are made explicit and open.
- The disequilibrium framework for modeling be established, where the adjustments, say in the need for variable 'A' in response to the

changes in the variable ‘B’ to new equilibria typically crate imbalances and transient behavior.

- Delays and other distortions in perceiving the true value of the variables be explicitly modeled.
- Desired and actual variables magnitudes be explicitly distinguished from real magnitudes in the model.
- Non-linear responses to actions be explicitly represented.

The significance of the modelling capabilities of system dynamics methodology is its contribution to our understanding of the structure and behaviour of complex, dynamic systems. An understanding of the relationship between the structure (s) and behaviour (s) leads to the formulation of a better mental model of the task system (Sterman, 2002) and improved decision making (Brekke and Moxnes, 2003; Romme, 2004).

Decision Support through the Interface Design

Dörner (1980) asserts that decisions makers in dynamic tasks must acquire some reasonably precise notions of relationships among key task variables and develop an understanding of the most influential delays and feedback loops in the task system. System dynamics methodology provides powerful tools to represent qualitatively the connections between structure and behaviour of the task system through (i) causal loop diagrams and (ii) stock and flow structures. Utilizing these tools together with advances in modern IT, powerful interface, whereby references to the underlying simulation model are facilitated interactively, in an ILE can be constructed (for an excellent illustration please see, Romme (2004)). In this way, ILEs aid decision making by allowing the learners to examine the structure-behaviour relationship as and when needed in an ILE session.

Decision Support through Tutor Support

Decisional aid in the form of human tutor support constitutes the distinguishing and fundamental component of an ILE model. In an ILE session, decisional aids can be provided at three levels: pre-, in-, and post-task levels. Pre-task level decisional aids can be conceptualized as information provided by the human tutor to a decision maker about the model of the task prior to performing the task (Corner, Buchanan, & Henig, 2001; Davidsen & Spector, 1997). In-task decisional aids attempt to improve the individuals’ decision-making performance by (i) making the task goals explicit at early stages of learning, (ii) helping them keep track of goals during the task, and (ii) providing them with ‘diagnostic information’ (Cox, 1992). Post-task level decisional aids aim at improving performance by providing the decision-makers an opportunity to reflect on their experiences with task (Cox, 1992; Davidsen & Spector, 1997). Thus, an ILE could support the user’s understanding of dynamic tasks by offering the opportunity to, experimentally, design, test, and evaluate their decision strategies.

Learning Assessment with ILEs

In addition to their role as decision support and leaning tool, ILEs can be used as an evaluation tool as well. We have developed such an ILE, FishBankILE, in which learners have access to decision variables that determine their task performance and task knowledge. Subjects also have access to relevant information that may support their decision making and learning. The implementation of FishBankILE allows unobtrusive measurement of subjects' decisions and decision rules. For instance, FishBankILE's underlying simulation model automatically captures the task performance metric of the leaner using the following algorithm:

> *The task performance metric is chosen so as to assess how well each subject did relative to a benchmark rule (a built-in routine in FishBankILE system). The task performance measure for subject s, TP_s has the following formulation:*

$$TP_S = \frac{\sum_{t=1}^{n_y} \sum_{t=1}^{n_T} \left| y_{it} - b_{it} \right|}{n_y * n_T}$$

> *where n_y is the number of performance variables, n_T is the number of trials the task has to be managed, b_{it} is the benchmark value of performance variable i at time t, and y_{it} is the empirical value of task performance variable i at time t. Task performance, TP, is assessed in the following way. Every decision period, the benchmark's performance variables' values are subtracted from the subject's. The subject's final performance, TP, is the accumulation over 30 periods of this difference, averaged over the number of task performance variables and number of trials*

In the next step of our project, we intend to use FishBankILE to asses the learning of students as well as professional program participants at our school.

Conclusion

Dynamic decision making research is highly relevant to both in-class learning and the managerial practice (Diehl & Sterman, 1995; Kerstholt & Raaijmakers, 1997). We need effective DSS to help the managers cope with the ever-present dynamic tasks. We presented ILE as a viable decision support and learning evaluation tool. Investigations regarding the overall effectiveness of ILEs, we believe, will advance our insights into the design conditions for an effective DSS to promote decision support and learning assessment in a variety of context.

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