Improving Decision Making and Learning in Dynamic Tasks Through Structured Debriefing-based Interactive Learning Environments: An Experimental Study

Abstract

The thesis of this article is that decision making and learning in dynamic tasks can be improved by helping individuals develop more accurate mental models of dynamic tasks through training with system dynamics–based interactive learning environments (ILEs) that include systematic debriefing. A laboratory experiment is reported in which participants managed a dynamic task by playing the roles of fishing fleet managers. It was found that process-oriented debriefing improved subjects' task performance, helped users learn more about the decision domain and develop heuristics. Groups with outcome–oriented debriefing and process-oriented debriefing did not differ on both decision time and decision strategy used by the subjects.

1. Introduction

Successful decision making is *raison d'être* of today's managers and policymakers. However, most of the managerial tasks are increasingly complex and dynamic in nature–a number of decisions are required rather than a single decision, decisions are interdependent, and the environment in which decision is set changes either autonomously or because of the decision made or both (Brehemer, 1990; Edwards, 1962; Sterman, 2000). For instance, managing a business firm, controlling the money supply, and achieving a sustainable use of renewable resources are all dynamic tasks. Improved decision making in these task would enhance the lives of individuals and the performance of organizations (Blazer et. al, 1989, Sterman, 2000).

In dynamic tasks, decision makers need ways to test their decision strategies before a costly and often irreversible implementation follows. ILEs provide a potential solution. For instance, ILEs are often used to improve decision making in dynamic tasks. We use "ILE" as a term sufficiently general to include micro worlds, management flight simulators, 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 decision making and learning. ILEs allow the compression of time and space and provide an opportunity for managerial decision making in a non-threatening way (Issacs and Senge, 1994). Despite an increasing interest in ILEs, recent research on their efficacy is inconclusive (Benbasat, and Nault, 1990; Bell et al., 2008; Davidsen, 2000; Faria, 1998; Plate, 2010). The increasing urge to improve the efficacy of ILEs has led the researchers to suggest improvements. One such way to improve the efficacy of an ILE is to incorporate *structured and systematic debriefing*.

For effective learning to occur, most of the learning activities with or without simulations require feedback. Prior research has shown that simple multiple-cue probability learning tasks can be learned by outcome feedback, complex cognitive tasks are not (Blazer et al., 1989). Debriefing is a special kind of feedback process whereby the decision makers are provided with an in-depth facilitation and reflection on their decision making experiences to improve their decision making skills in, cognitively intensive, dynamic tasks (Dreifuerst, 2009; Fanning and Gaba, 2007: Lederman, 1992).

In the context of dynamic tasks, a debriefing is a time to reflect on the learning experiences gained from an ILE. Debriefing is the processing of simulation-based learning experience from which the decision-makers are to draw the lessons to be learned (Lederman, 1992; Stienwachs, 1992). Debriefing is delivered in different forms and methods. Oral discussions, written notes, debriefing games are the most common variants (Lederman, 1992; Stienwachs, 1992; Vissers and Peters, 2004). In an oral discussion, learners and debriefer engage in a question and answer session designed to guide learners through a reflective process about their learning. In written notes, a passive form of debriefing, the learners are provided with hand-outs that present “expert solution” to the task they had in the ILE and examples of potential applications of their learning. Debriefing games are interactive strategies, played through computer or board games where the learners are encouraged to reflect on earlier events (Thiagarajan, 1992). Debriefing sessions can be organized in two ways: (i) where participants are presented with a sort of “expert solution” to the task in the ILE and are asked to recall, reflect, and compare their “own” solutions (Lederman, 1992; Stienwachs, 1992; Peters and Vissers, 2004; Qudrat-Ullah, 2010), and (ii) where participants are led through a process that illustrates the underlying structure of the task systems and how it relates to the behavior of the task system (Cox, 1992; Crookall et al., 1987; Spector 2000; Qudrat-Ullah, 2007). We term former as “outcome-oriented debriefing” and later as “process-oriented debriefing”. This distinction is important as for well-structured and well-learned tasks, outcome-oriented debriefing alone may be sufficient to stimulate performance improvements. When a task embodies uncertainties, process-oriented debriefing should help the learners to overcome the misconceptions about the task. Also, debriefing plays fundamental role in helping the participants connect the knowledge and skills developed in a simulation session to the corresponding real life situation—*transfer learning* (Peters and Vissers, 2004; Dreifuerst, 2009; Fanning and Gaba, 2007; Gonzales and Cathcart, 1995; Lane and Tang, 2000). Therefore, we assert that learners in our debriefing-based ILE will have the opportunity to develop such transfer learning skills.

In summary, previous studies provide an insight into the effectiveness of debriefing to decision making and leaning in ILEs. However, with the exception of a single study (Qudrat-Ullah, 2007), prior studies, have explored, only theoretically, how debriefing may contribute to decision making processes. Several gaps still remain, for instance, (i) measures of effectiveness of debriefing lack a comprehensive framework, (ii) the effects of various forms of debriefing (e.g., outcome-oriented, process-oriented) are unknown, (iii) no empirical evidence on how debriefing effects the decision making process. This project aims to bridge some of these gaps and advance previous research by proposing and using a comprehensive research model aimed at evaluating the effectiveness of structured and systematic debriefing on both the decision making *process* and the decision *outcome* in an ILE.

2. Theoretical Premise and Hypothesis Development

To perform better in dynamics tasks, decision makers need to develop an adequate model of the task (Conant and Ashby, 1970; Sterman, 2000; Qudrat-Ullah and Karakul, 2007). Outcome-oriented debriefing does not provide enough information to the participants to enable them form a suitable model of the dynamic task (Blazer et al, 1989; Sengupta and Abdel-Hamid, 1993; Sterman 1989). Individuals need to understand both the *delays* and the *feedback structures* underlying the task. Process-oriented debriefing, however, has the potential to impart this crucial knowledge: the debriefer identifies the feedback structures and their relation to the outcomes, delays are examined, and uncertainties are discussed.

Sengupta and Abdel-Hamid (1993), on the other hand, found that subjects provided with cognitive feedback-information provided to the decision makers to improve their decision making capabilities by enhancing their comprehension of the task structure, employed consistent decision strategies and performed better than those provided with outcome feedback alone. Process-oriented debriefing, with the potential to aid the decision makers develop a suitable model of the task (Conant and Ashby, 1970; Zydney, 2010), should induce decision makers to adopt consistent decision strategies and perform better. However, this increased understanding of the task system comes at the expense of increased cognitive effort expended (e.g., in systematic exploration and testing of hypotheses regarding the relationship between systems variables) (Kirlik et al., 1995). On the other hand, outcome-oriented debriefing where expert solution is presented, subjects might mimic and use the presented heuristic and become efficient in decision making.

3.0 Methodology

We designed a single factor, completely randomized design involving one control group and two experimental groups. Each participant in the experimental group used FishBankILE with either process-oriented or outcome-oriented debriefing. Debriefing was delivered in a scripted discussion between the debriefer and the participants, after the participants have completed 1st

formal trial of the task. We conducted the experiment with 93 to 99 executive-MBA program participants, recruited from three local Canadian universities. A pre-test questionnaire was used to control subjects' background education, knowledge, and demographics. The computer program embedded in FishBankILE allowed the automatic capture of users' decisions data and task performance.

The Task. In the dynamic task, subjects played the role of fishing fleet managers making fleet capacity acquisition and utilization decisions. Each year subjects was required to order new ships and decide the utilization of the fleet. Task performance is measured by cumulative profits.. The dynamic behavior in the model arises due to two fundamental accumulation processes: accumulation of ships and stock of the common resource-fish.

Catch per ship drives the profitability for the firm. The increased profits provide incentives for fleet expansion. A diminishing rate of fish catch may trigger the lay-up of the existing ships. The catch per ship is a function of the fish density of the fishing area. The relationship between the fish density and the fish catch per ship is non-linear. The current stock of fish determines the fish density. Fish catch depletes the fish stock, while fish generation adds to the stock.

Procedures. All subjects were supplied with a folder containing the consent form, instructions to lead them through a session, training materials for the task, notepads, and pens as they will be encouraged to take notes along the experiment. The experiment started with each participant returning the signed consent form and taking a pre-test on task knowledge. Then the experimenter provided an introduction to the task system and the experiment. All the groups received the same general instructions.

All the subjects completed a training trial, making decisions in each period, accessing and observing the feedback of their decisions via graphs and tables. Then, all the subjects completed two formal trials interceded by either a small break for the control group (no discussions was allowed) or a debriefing activity for the experimental groups.

Independent Variable is the "availability of debriefing" in an ILE. **Dependent Variables** are task performance, structural knowledge, heuristics knowledge, and cognitive effort. The task performance metric is chosen so as to assess how well each subject did relative to a benchmark rule.

. 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. A post-test questionnaire measured the structural knowledge through fourteen closed-ended questions on the relationships between pairs of the task variables. Two open-ended questions asked the subjects about their general strategy for ordering new ships and ships utilization. Two independent domain experts graded the answers. The average scores on the two questions measured the heuristic knowledge. Decision time was measured as the time spent by a subject making decisions in each of the decision periods (excluding the time it took to run the simulation).

4. Results

There were no significant differences across treatments (i.e., one control group and two experimental groups) with respect to gender (p = 0.870 both for males and females), age (F (2, 96) = .23, p = 0.798), prior structural knowledge (F (2, 96) =14, p = ..657) and heuristics knowledge (F (2, 96) = 0.876, p = 0..878) about the task system. Likewise, all the groups did not differ in terms of their background education.

There was significant difference among the three groups (i.e., Group 1: No Debriefing, Group 2: With Outcome-oriented Debriefing, and Group 3: With Process-oriented Debriefing) when considered jointly on the variables of decision making (i.e., task performance, decision time, and decision strategy) and learning (structural knowledge, and heuristics knowledge),

Table 2: Between-Subjects Effects

Dependent Variable	*p-value*
Task Performance	0.000
Decision Time	0.000
Decision Strategy	0.000
Structural Knowledge	0.000
Heuristics Knowledge	0.000

We conducted planned contrast analysis among all the three groups on all the dependent variables. Compared with the group with no debriefing, all the treatment groups performed significantly better on task performance, so the hypothesis H1a is strongly (p=0.000) supported. Also, the hypothesis H2a, group with process-oriented debriefing achieved better task performance than the group with outcome-oriented debriefing. However, on decision time, H2a is supported but H2b is not supported: contrary to the hypothesis, group with process-oriented debriefing, where the subjects were expected to spend more time say in focusing on structure-behavior patterns of the key variables, spent less time than those with outcome-oriented debriefing.

On task knowledge performance, the hypotheses H4a, H4b, H5a, and H5b were strongly supported too. The process-oriented debriefing group performed the best both on structural and heuristics knowledge. Group with no debriefing did not show any statistically significant improvement in their task knowledge.

5. Concluding Remarks

It is interesting to note that despite the overwhelming evidence of the effects of debriefing on subjects' task performance, none of the groups did (statistically) better that the bench mark rule. In fact, it would be naïve to think that subjects will become expert on dynamic decision making as result of couple of trials. This implies that we should look at broader measures of task performance in dynamic tasks. Overall, we find positive impact of debriefing on subjects' decision making and learning about a dynamic task.

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