MAXIMIZING THE POTENTIAL OF TRANSPARENT SIMULATIONS BY COMBINING PERFORMANCE GOALS WITH LEARNING GOALS AND EXPLORATORY GUIDANCE IN A DYNAMICALLY COMPLEX TASK

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ABSTRACT

Simulation-based learning environments have been proposed by researchers, as educational tools to support learning in complex business systems. However, studies have evidenced that subjects may nevertheless have great difficulty understanding and managing dynamic systems. Previous research has revealed positive learning and performance effects of using transparent simulations (that is, revealing users the structure and behaviour of the simulator model). This study explores the effects of combining exploratory guidance, learning goals, and performance goals in a transparent simulation of a dynamically complex system. We present a set of hypotheses about the influence of different goal-setting conditions on participants' performance and comprehension of the system dynamics. In a simulation experiment, participants interacted with a system dynamics model representing the growth of a business venture. Participants who previously worked higher learning goals under exploratory guidance and were then submitted to higher performance goals (compared to vague goals) achieved higher performance and demonstrated better comprehension of the model dynamics. However, participants who were only subjected to more specific, high performance goals (compared to vague performance goals) did not improve their outcomes and revealed larger differences within the treatment group. Two out of the four hypotheses were confirmed. In a transparent simulation of a dynamically complex system, setting specific, high learning goals, previously worked through exploratory guidance, positively moderates the impact of the level of performance goals on the comprehension of the model dynamics and performance.

KEYWORDS

Simulation-Based Learning, System Dynamics, Model Transparency, Exploratory Guidance, Discovery Learning, Goal-Setting Theory

1. INTRODUCTION

1.1 Model Transparency

Simulator transparency refers to the extent the structure and behaviour of the underlying computational model is shown to students using the simulation. In "black-box" or opaque simulations, students can explore a system's behaviour, but the underlying computational models remain hidden and can only be inferred by what appears on the screen. Studies have suggested that this type of ''black-box'' situation could lead students to form wrong mental models, interfering with proper learning. "Glass-box" or ''transparent'' simulations have alternatively been proposed to obviate the above-described problems, as the relations among their variables are accessible to students. Transparent simulators have been used in system dynamics (SD) learning environments, detailing through their stocks-and-flows diagram (SFD) the causal structure of the underlying system. By using this approach, students may trace the cause and effect structure and understand the relationships between structure and behaviour, and they are in a position of understanding even counterintuitive system behaviours.

Research shows that structural knowledge provided by transparent simulations has the potential to improve leaning and task performance (Capelo and Silva, 2020).

1.2 Learning and Performance Goals in Complex Tasks

The goal setting, a theory of motivation in organizational psychology, states that setting specific and high goals leads to higher performance than easy goals, no goals, or even general goals, namely "to do one's best" (Locke & Latham, 2013). The assumption in the education is that a simulation task with no clear learning and performance goals may disorient and fail to stimulate students' attention and interest. The positive effects of goals operate through cognitive and affective mechanisms, including attention, effort, persistence, self-efficacy, motivation, and learning (Locke & Latham, 2013). In this context, goal setting is viewed as a promising technique to provide attention and motivation towards learning and to avoid situations in which the students merely play the game (Nebel et al., 2017). Goals stimulate cognitive activities to support simulation-based learning such as attending to instruction, developing task strategies to attain the goals, and processing and integrating relevant knowledge (Yang et al., 2017).

On the other hand, previous studies have shown that providing no specific goals at all could benefit learning in problem-solving tasks (Sweller, et al., 1998). According to the cognitive load theory (CLT) (Sweller, 2020), learning is compromised when the total cognitive load exceeds available working memory capacity. That goal-free effect, which is derived from CLT, states that learning and performance will improve by setting vague goals, and thus avoiding unnecessary load resulted by distant, specific goals (Sweller et al., 1998). These cognitive costs may generate distraction and deteriorate students' learning and performance outcomes (Crouzevialle & Butera, 2017). Gary et al. (2017) did not find main effect of stretch goals on performance and concluded that stretch goals (compared with moderate goals) generate large attainment discrepancies that increase willingness to take risks, undermine goal commitment, and generate lower risk-adjusted performance.

Goal-setting theory distinguish two types of goals (Locke & Latham, 2013): learning goals, which focus on acquiring the required task knowledge, and performance goals, which specify desired task outcomes. Performance goals may lead to the situation in which students only attempt to reach their goals rather than acquiring the knowledge and skills needed. Whereas learning goals may lead to more learning-oriented behaviour such as focussing attention on mastering a task, discovering task-relevant strategies, and achieving learning objectives. The results of Nebel et al. (2017) showed that specific learning goals decrease cognitive load and improve motivation.

In a complex task, learners lack the necessary knowledge to perform effectively because task elements are highly interrelated, and the consequence of possible actions is often ambiguous (Gary & Wood, 2011). Empirical studies revealed that when there is a high complex task that requires previous learning so that it can be performed effectively, a general goal (e.g., ''to do one's best'') leads to better outcomes than a specific performance goal. In that stage, wherein the requisite knowledge needs being acquired, the approach proposed consists of assigning learning goals first, and then assigning performance goals later once subjects sufficiently learn about the task (Chen & Latham, 2014; Latham et al., 2008; Yang et al., 2017).

1.3 Exploratory Guidance and Discovery Learning

Simulation-based learning is frequently considered a method to promote inquiry-based learning and discovery learning (Alfieri et al. 2011). However, the literature on simulation-based learning suggests that students perform better when some form of guidance is provided (Landriscina, 2013). Instructional guidance refers to the support provided to students during simulation in the form of questions, procedures, steps, or materials. According to Mayer (2004), instructional methods involving guided discovery have been more effective in helping students learn, as they involve cognitive activity. In such instructional strategy, students discover the underlying rules through exploratory guidance, this is, at each stage, learning goals are presented, and students are free to explore the learning environment. Studies have found that students achieve deeper understanding of subject matter when using scientific reasoning (Clement, 2008). They have the opportunity to iteratively act, appreciate the consequences of their decisions, reflect, and test their comprehension of the cause-effect relations.

However, some studies on inquiry learning with computer simulations (e.g. de Jong, 2006) have shown that students operating in complex environments generally have difficulty in all phases of the inquiry process. In a simulation task, the complexity of the model may exceed the working memory limits of students. To obviate these cognitive load problems, de Jong et al. (2018) suggest that instructional method be integrated with ‘cognitive tools’ aimed at guiding and supporting students’ activities. More recently, the results of the experiment conducted by Capelo and Silva (2020) indicated positive learning effects of using transparent simulations and exploratory guidance involving model progression, worked examples, and task segmentation. Debriefing sessions may also be incorporated in the instructional method, by discussing with the students about their difficulties related to the comprehension of the model structure and behaviour (between simulation runs). This approach can stimulate students to reflect on the simulation experience and help them to overcome misconceptions about dynamic and complex tasks (Capelo et al., 2020).

2. RESEARCH HYPOTHESES

The present study investigates whether an instructional approach of simulation-based learning that includes exploratory guidance, learning goals, and performance goals can improve the learning potential of transparent simulations in a dynamically complex task, which consists of starting and growing a business venture.

According to a model-based learning perspective, the learnings outcomes refer to the students’ comprehension of the simulated system and to their performance in the simulation task. The students’ comprehension is assessed on the basis of their ability to deal with specific dynamic aspects of the simulation model. As students interact with the simulator dynamics, they interpret the situation, mentally simulate the consequences of selected actions, and then they define and implement courses of action which reflect their comprehension about the structure and behaviour of the simulator model.

The expected relations and hypotheses are based on the following variables: (i) LPG - Level of Performance Goals. This variable indicates in what extent the instructional method includes the setting of specific, high performance goals. (ii) LLGEG - Level of Learning Goals and Exploratory Guidance. This variable indicates in what extent the instructional method includes the setting of specific, high learning goals, worked under exploratory guidance. (iii) Comprehension of model dynamics (CMD). This variable reflects how students comprehend the structure of the simulation model and are able to infer its dynamical behaviour. (iv) Performance. The performance of this simulation task is measured in terms of the financial value created by the venture.

The following hypotheses are defined: H1a - LPG positively influences CMD; H1b - LPG positively influences Performance; H2a - LLGEG positively moderates the effect of LPG on CMD; H2b - LLGEG positively moderates the effect of LPG on Performance.

3. METHOD

3.1 Simulator, Participants, and Procedure

The SBLE used in this experiment incorporates a system dynamics (SD) model that was developed and utilized in previous research (Capelo et al., 2018; 2020), which represents the growth of a business venture. By interacting with this simulator, students would be able to appreciate the dynamical complexity involved in a business venture and the performance effects caused by system misconceptions. The SBLE provides a transparent interface, which includes six screens. The first screen (the panel control) allows participants to adjust simulation parameters and includes tables presenting critical measures. The panel control provides the information included in a stock and flow diagram. The second and third screen present the historical behaviour over time for key variables. The other screens show the causal loop diagram (CLD) and selected stock and flow diagrams (SFDs) of the simulator model.

In order to test the hypotheses, we conducted a laboratory experiment using three treatment groups: a control group (CG) of students who interacted with a transparent simulator, without learning and performance goals - low LPG and low LLGEG; an experimental group (E1) of students who used a transparent simulator, had performance goals, and did not have learning goals - high LPG, and low LLGEG; and an experimental group (E2) of students who used a transparent simulator, had performance goals, and had learning goals previously worked under exploratory guidance - high LPG, and high LLGEG.

This research was conducted at Iscte Business School in Lisbon, Portugal. The experiment involved three classes of entrepreneurship courses with 68 students in total. Groups CG (with 22 students), E1 (with 24 students), and E2 (with 22 students). One of the authors acted as instructor in these classes.

To succeed in this simulation task, students need to identify and understand the cause-and-effect relationships among critical variables, particularly those included in the CLD and selected SFDs provided in the simulator interface. That model complexity has been demonstrated to negatively influence both formation of accurate mental models and task performance. Moreover, subjects who are not familiarized with systems dynamics have additional difficulties in recognizing and comprehending dynamical structures as they are not able to properly read and interpret causal-loop-diagrams and stocks-and-flows diagrams (Davidsen & Spector, 2015). In order to obviate these problems, model transparency is complemented with structural and behavioural debriefings (Capelo et al., 2020). The students from all the groups participated in a debriefing session (after the first simulation run) focused on the model variables and relations. Then (after the second simulation run) they were involved in discussions about the relation between model structure, courses of action, and behaviour.

The experiment procedure involved two sessions and had the following steps (Figure 1).

Treatment		Experimental Procedure								
		a) Lecture on CLD and SFD	b) Simulator and task description	c) First simulation run	d) Structural debriefing	e) Second simulation run	f) Behavioural debriefing	g) Learning goals and simulation with exploratory guidance	h) Performance goals	i) Third simulation run
CG	Low LPG, low LLGEG	●	●	●	●	●	●			●
E1	High LPG, low LLGEG	●	●	●	●	●	●		●	●
E2	High LPG, high LLGEG	●	●	●	●	●	●	●	●	●

Figure 1. Experimental procedure

Session 1. a) The students received a lecture on CLDs and SFDs, so that they were able to read and interpret the CLD and SFDs available in the simulator interface. During the simulation task, all the participants were encouraged to read and interpret the CLD and SFDs available in the game interface.

Session 2. In this session, students performed the simulation task using three simulation runs (for approximately 20 to 25 minutes each). b) They read the introduction with the overall description and the objectives of the simulation task. Participants then read the instructions for accessing, starting, and running the simulator. Some simulation rounds were conducted to become familiar with the simulation. c) They performed the first simulation run. d) The students, after performing the first simulation run, participated in a structural debriefing (lasting approximately 35 minutes). The instructor described the CLDs and SFDs in the game interface in a form of a step-by-step guided tour and cleared all the doubts raised by students concerning the model variables and their relations. e) Participants then performed the second simulation run. f) The second simulation run is followed by a behavioural debriefing. This debriefing (lasting approximately 50 minutes) focused on the relation between the model structure, courses of action, and corresponding dynamical behaviour. g) The students from experimental group E2 (submitted to learning goals, exploratory guidance, and performance goals) were assigned some specific learning goals related to three different simulation phases. For each simulation phase, they were asked to identify and write a description of a possible strategy to overcome certain challenges and maximize value creation. The participants were free to explore the simulator, performing all the simulation runs they need. They analysed the challenges to be addressed, hypothesised strategies and scenarios, adjusted the decision parameters, ran the simulator, interpreted the results, defined new strategies and scenarios, and repeated the process. Once students identified and wrote down the strategy requested, they moved to the next simulation phase. They spent approximately 60 minutes working through the three simulation phases. h) The participants from experimental groups E1 (submitted to performance goals) and E2 (submitted to learning goals, exploratory guidance, and performance goals) were given high performance goals to be addressed in the final simulation round. i) Finally, they performed the third and final simulation run. The students from group E2 were asked to implement the strategies they had identified in order to achieve the performance goals.

3.2 Research Variables

This section summarises the use of the variables that were defined in the research model.

Level of Performance Goals (LPG). This variable features two degrees. In the low degree, students perform the simulation task with a global, vague performance goal. They are to maximize value creation. In the high degree, students have specific, high performance goals. They are to achieve certain outcomes in terms of clients and value creation for each simulation phase.

Level of Learning Goals and Exploratory Guidance (LLGEG). This variable features two degrees. In the low degree, students perform the simulation task without specific learning goals and they are not submitted to exploratory guidance. In the high degree, the students are submitted to specific, high learning goals, combined with exploratory guidance. They are free to explore the simulator, performing all the simulation runs they need. This experiment condition is designed to promote discovery learning with appropriate aids. They are asked to identify and test strategies to address specific business challenges. The students reflect on each issue, formulate some hypotheses about model behaviour, and define scenarios to test those hypotheses. They run the simulator, interpret the results, test the hypotheses, and determine the cycle repeats.

Comprehension of the model dynamics (CMD). This variable indicates how students understand the structure and behaviour of the simulation model. The measurement of this variable is based on students' patterns of action throughout the final simulation round, by analysing how they consistently deal with certain dynamical structures of the simulation model. This variable is calculated as the average of four components that are rated in a continuous scale (from 0 to 1) against reference values.

Performance. The performance of this simulation task is measured in terms of the financial value created by the venture, indicated by the value of the parameter MVA (market value added) achieved in the final simulation round. This variable is rated in a continuous scale (from 0 to 1) against reference values of MVA.

4. RESULTS AND DISCUSSION

Table 1 presents the mean values, standard deviations, and sample sizes for the variables CMD and Performance corresponding to the three experimental treatments. Table 2 displays the results of an independent sample *t* tests of significance for differences in means between pairs of treatment groups.

The lowest mean values for the variables CMD and Performance were found in participants from experimental group E1 (submitted only to high performance goals). On average, the participants from group E2 (submitted to high learning goals, exploratory guidance, and high performance goals) exhibited the highest values for both the dependent variables. These results suggest that participants learn and perform more effectively if the transparent simulation combines specific, high learning goals, previously worked under exploratory guidance, with specific, high performance goals.

The students from control group (CG) and those from the group E1 (submitted only to high performance goals) were submitted to equivalent guidance conditions. The difference between those treatment groups is that while students from control group had a vague performance goal (to maximize value creation), students from group E1 had specific, high performance goals to be achieved throughout the simulation task. The statistical testing presented in Table 2 (pair E1-CG) shows that the average outcomes from those groups are not significantly different (CMD mean difference = -0.070, $p = 0.117$; Performance mean difference = -0.097, $p = 0.157$). The comparison between treatment groups CG and E1 presented in Tables 1 and 2 demonstrates that setting high performance goals did not cause the participants to reveal better outcomes. Instead, high performance goals compared with vague performance goals increased the variance in CMD and performance. That means that participants from group E1, who received specific, high performance goals for each phase throughout the simulation task, on average, did not improve their comprehension of the model dynamics and performance, and revealed larger differences within the treatment group. One possible explanation is that some students may lack of proper knowledge about the complex structure and behaviour of the simulator model in order to effectively deal with those high performance goals. Thus, those students from group E1, in such poor understanding condition, may experience additional pressure and cognitive load as they monitor their progress and perceive a persistent and increasing distance from the desired performance level, which reduce the availability of their limited cognitive resources. These cognitive costs may generate distraction and deteriorate learning and performance outcomes, which erodes motivation and goal commitment. These findings are somehow consistent with the results reported by Gary et al. (2017) that, in a complex task, stretch goals (compared with moderate goals) did not produce a significant main effect on performance and increased its variance.

Table 1. Means and standard deviations for variables CMD (comprehension of model dynamics) and Performance for each treatment group

			CMD - Comprehension of the Model Dynamics		Performance	
Treatment	Description	N	Mean	SD	Mean	SD
CG	Low LPG, low LLGEG	22	0.458	0.144	0.455	0.196
E1	High LPG, low LLGEG	24	0.388	0.153	0.358	0.254
E2	High LPG, high LLGEG	22	0.564	0.122	0.622	0.259

LPG - Level of Performance Goals; LLGEG - Level of Learning Goals and Exploratory Guidance

Table 2. Independent sample t-tests of significance for differences in means for the variables CMD and Performance between pairs of treatment groups

	CMD - Comprehension of the Model Dynamics			Performance		
Pair	Mean Difference	SD	p-value	Mean Difference	SD	p-value
E1-CG	-0.070	0.044	0.117	-0.097	0.067	0.157
E2-CG	0.105*	0.040	0.012	0.167*	0.069	0.021
E2-E1	0.176**	0.041	0.000	0.264**	0.076	0.001

*p<0.05, **p<0.01

On the other hand, the difference between treatment groups E1 and E2 is that students from the latter group received previously some specific challenges and learning goals to be addressed through exploratory guidance. As shown in Table 2, the comparison between group CG and group E2 (pair E2-CG) reveals positive differences in means for CMD and Performance (CMD mean difference = 0.105, p = 0.012; Performance mean difference = 0.167, p = 0.021). Consequently, the variable LLGEG seems to positively moderate the impact of LPG on CMD and Performance. Students submitted to high performance goals demonstrate, on average, an increasing comprehension of the model dynamics and a better performance if they addressed previously high learning goals through exploratory guidance. As students explored the simulator to resolve the challenges associated to the learning goals, they were engaged in an inquiry process and had opportunity to accelerate and consolidate their learning about the structure and behaviour of the simulated system.

Table 3 shows the results of multivariate regression analyses of CMD and Performance on the independent variables. The regressions were run on standardised values for all the variables to directly compare the relative effects of each independent variable on the dependent variable. As presented in Table 4, regression analysis for CMD on the independent variables shows a low significant negative effect for LPG (β=-0.212, p=0.095) and no significant effects for LLGEG (β=-0.176, p=0.174). Regression analysis of

Performance shows strong significant positive effects for LPG (β=0.529, p<0.001) and LLGEG (β=0.4792, p<0.001).

In the present teaching approach and corresponding experiment design, the learning goals and exploratory guidance are applied as complementary methods to increase the effectiveness of performance goals setting. Thus, high LLGEG only occurs with high LPG. Consequently, we are only able to identify moderation effects of LLGEG on the relation between LPG and CMD/Performance. As such, the significant positive correlation found between LLGEG and CMD/Performance means that LLGEG positively moderates the relation between LPG and CMD/Performance.

Table 3. Regression results for all independent variables

	Dependent Variables			
	CMD - Comprehension of Model Dynamics		Performance	
Independent Variables	Stand. Beta	p-value	Stand. Beta	p-value
LPG - Level of Performance Goals	-0.212*	0.095	-0.176	0.174
LLGEG - Level of Learning Goals and Exploratory Guidance	0.529**	0.000	0.479**	0.000
Adjusted R^2	0.194		0.154	

*p<0.1, **p<0.01

These results confirm two of the four hypotheses. As indicated by Table 2, the mean values of CMD and Performance for experimental group E1 (high LPG and low LLGEG) are not significantly different from those for the control group (low LPG and low LLGEG). Also, the regression (Table 3) does not show significant positive effects (at 0.05 significance level) of LPG on CMD and Performance. On contrary, regression for CMD reveals a low significant negative effect for LPG (at 0.1 significance level). Consequently, our research does not provide support for hypotheses H1a/b - the level of performance goals positively influences the comprehension of the model dynamics and the performance in transparent simulations of a complex system. As discussed previously, the results presented in Table 2 suggest that LLGEG positively moderates the impact of LPG on CMD and Performance. Additionally, as the learning goals and exploratory guidance condition (high LLGEG) complements the performance goals condition (high LPG), a significant effect of LLGEG on CMD and Performance (Table 3) also confirms the existence of that moderation effect. Consequently, these findings support hypotheses H2a/b - the level of learning goals and exploratory guidance positively moderates the impact of the level of performance goals on the comprehension of the model dynamics and on the performance in transparent simulations of a complex system.

5. CONCLUSION

This study is based on an educational experiment aimed at testing hypotheses about the effects of setting learning and performance goals on students' learning and task performance in a transparent simulation of a dynamically complex system. It was predicted that (1) setting specific, high performance goals (compared to vague, moderate performance goals) and (2) setting additionally specific, high learning goals, previously worked through exploratory guidance, would benefit learning and task performance, in a transparent simulation of a dynamically complex system.

The results from regression analysis confirm two of the four hypotheses. The hypotheses H1a (the level of performance goals positively influences the comprehension of the model dynamics) and H1b (the level of performance goals positively influences the performance) are not supported. This finding is consistent with some of the literature on learning from complex simulations. For example, Gary et al. (2017) also reported that, in a complex task, stretch goals (compared with moderate goals) did not produce a significant main effect on performance. A possible explanation, in the view of CLT, is that the extra pressure and cognitive load, caused by the persistent and increasing distance from the high goals, reduce the availability of students' cognitive resources, deteriorate learning and performance outcomes, and erode motivation and goal commitment.

By previously working specific, high learning goals, under exploratory guidance, students significantly improved comprehension and task performance, supporting hypothesis H2a (the level of learning goals and exploratory guidance positively moderates the impact of the level of performance goals on the comprehension of the model dynamics) and H2b (the level of learning goals and exploratory guidance positively moderates the impact of the level of performance goals on the performance). As we hypothesised, the results strongly evidence that setting specific, high learning goals (to be previously worked under exploratory guidance) gave participants a powerful means to reflect and learn on model structure and behaviour, which accelerated and consolidated their learning about the dynamics of the simulated system and enhanced performance. This conclusion is in line with previous research about the goal setting effects on performance in high complex tasks (e.g. Chen & Latham, 2014; Latham et al., 2008; Yang et al., 2017), which articulates that in situations where primarily the acquisition of knowledge and skills is required, a specific challenging learning rather than an outcome goal should be set.

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