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Exploring the effects of setting performance and learning goals in a transparent simulation of a dynamically complex task

ABSTRACT

Simulation-based learning environments are increasingly viewed as promising tools to foster learning in complex domains. However, research has indicated that subjects may nevertheless have persistent cognitive difficulties in comprehending and managing dynamic systems. Previous studies have revealed positive learning effects of using transparent simulations (that is, revealing to 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. In a simulation experiment, participants interacted with a system dynamics model representing the growth of a business venture. Participants who had previously worked higher learning goals under exploratory guidance and were then given higher performance goals achieved higher performance and demonstrated better comprehension of the model dynamics. However, participants who were only subjected to more specific, high performance goals did not improve their outcomes and revealed larger differences within the treatment group.

KEY WORDS

Simulation-Based Learning, Goal-setting Theory, Exploratory Guidance, Model Transparency, Business Simulation, System Dynamics

1. INTRODUCTION

Simulation-based learning environments (SBLEs) are promising tools to support learning in complex domains (Cunico et al., 2022; Davidsen & Spector, 2015; Groesser, 2012; Landriscina, 2013; Maier & Größler, 2000; Sterman, 1994). A significant body of research based on simulation experiments has also revealed that subjects have difficulty in perceiving dynamic complexity correctly (e.g. Aşık & Doğança Küçük, 2021; Hendijani, 2021; Kampmann & Sterman, 2014; Ozgun & Barlas, 2015; Sterman & Dogan, 2015; Stouten & Größler; 2017; Strohhecker & Leyer, 2019).

Traditional SLBEs are typically of the opaque or black-box type where the structure of the simulation model is concealed from learners. Conversely, transparent or 'glass-box' SBLEs enable learners to visualize the variables and relations included in the simulation model (Landriscina, 2013). The use of transparent simulations has been proposed to obviate the problem of developing misinterpretations of the model structure and behaviour. The implicit promise is that model transparency enhances learning and performance as students will be able to identify and comprehend the critical variables and relationships that mainly determine the behaviour of the simulated system (Groesser, 2012; Milrad et al., 2003). Previous research about the effects of model transparency on learning and performance has produced mixed or inconclusive results (Capelo & Silva, 2020; Cheverst et al.,2005; Größler et al., 2000; Kopainsky & Alessi, 2015; Machuca, 2000). Furthermore, some studies have suggested that model transparency may only benefit learning and performance when it is combined with other instructional strategies such as causal diagramming (Capelo & Dias, 2009; Gary & Wood, 2016), model exploration (Capelo & Silva, 2020; Kopainsky et al., 2015), model progression (Elsawah et al., 2017; Van Borkulo et al., 2012), worked examples (Mulder et al.; 2015), discussions or debriefing sessions (Capelo et al., 2021; Qudrat-Ullah, 2007, 2014, 2020), and challenging goals (Yang et al., 2017; Yang et al., 2018). This leads to the following research question - what type of instructional support needs to be offered in order for learners to be able to take full advantage of transparent simulations? Therefore, to contribute to the necessary deepening of this line of research, the present study aims to explore the effects of combining

exploratory guidance, learning goals, and performance goals in a transparent simulation of a dynamically complex system.

2. LITERATURE REVIEW

2.1 Simulation-based learning environments

Modelling and simulation approaches have been widely used to support learning and decision-making on complex management issues. In terms of the decision-making process, the literature shows important advances in the development and application of modelling and simulation techniques to enable decision makers to tackle complex problems and find optimal solutions. (e.g. Cao et al., 2023; Kou et al., 2021; Kou et al., 2022; Xiao et al., 2023).

On the learning aspect, modelling and simulation approaches have also supported the development of environments that allow subjects to learn about complex issues in a safe and controlled way. Simulation-based learning (SBL) or model-based learning (MBL) refers to the activity of humans interacting with an external, formal model (simulation model) for the purpose of learning (Groesser, 2012; Landriscina, 2013). The literature provides evidence that simulation-based learning environments (SBLE) are effective in supporting learning in complex domains (Davidsen & Spector, 2015; Groesser, 2012; Landriscina, 2013; Maier & Größler, 2000; Palmunen et al., 2021; Sterman, 1994). According to Groesser (2012), SBLEs provide a means through which learners can iteratively experiment, develop, and test their comprehension of complex problems, thus resulting in the more accurate mental models required to build competence, confidence, and expertise (Davidsen & Spector, 2015; Sterman, 1994). Particularly, simulation tasks have been increasingly included in business education activities (Faisal et al. 2022; Farashahi & Tajeddin, 2018; Goi, 2019; Hallinger & Wang, 2020; Obi et al., 2022). The various benefits of simulation-based learning in higher education reported in the literature (Campos et al., 2020; Chen et al., 2023; Huang et al., 2023; Samaras et al., 2022; Uzun & Uygun, 2022) include: increased student motivation; acquisition of knowledge in a safe environment; and the fostering of entrepreneurial attitudes, learner engagement,

collaborative work skills, critical thinking, problem solving and decision making. Vlachopoulos and Makri (2017) highlighted the affective effects prior to cognitive processes, emphasising motivational and engaging factors that lead to emotional development, satisfaction, self-efficacy and self-assessment.

2.2 Model transparency

Simulator or model transparency is related to the ability of the SBLE to enable students to identify and comprehend the critical assumptions, variables, and relationships that mainly determine the behaviour of the simulated system. A low transparency situation occurs in opaque or 'black-box' SBLEs, in which the structure of the computational model is not revealed to users. In such cases, students can only infer the structure and behaviour of the underlying computational model by what appears on the SBLE interface. Studies have suggested that this type of model transparency could lead students to build inaccurate mental models, and thus interfere with proper learning (Landriscina, 2013). A higher transparency situation is associated with transparent or "glass-box" SBLEs. As students interact with the simulator, students are able to access the critical variables and relations that mainly explain the model behaviour. This approach may help learners to better understand the relationship between the structure and behaviour of complex systems (Groesser, 2012; Milrad et al., 2003).

System dynamics (SD) is a modelling and simulation approach that allows transparent SBLEs to be built as they provide stock-and-flow diagrams (SFDs) which make the relations among the model variables visible (Groesser, 2012). However, according to Davidsen and Spector (2015), in order to take advantage of SD models' transparency, students must be able to interpret a stock-and-flow diagram.

The literature suggests that transparent simulations may affect learning and performance (Capelo & Dias, 2009; Capelo & Silva, 2020; Capelo et al.,2021; Cheverst et al.,2005; Elsawah et al., 2017; Gary & Wood, 2016; Größler et al., 2000; Kopainsky & Alessi, 2015; Kopainsky et al., 2015; Machuca, 2000; Mulder et al.; 2015; Qudrat-Ullah, 2007, 2014, 2020; Van Borkulo et al., 2012). Machuca (2000) found that transparent simulations favour management learning of organisational complexity. Größler et al. (2000) investigated the

performance effects of model transparency when students used a business simulator. They concluded that familiarity with the model structure led to better performance. However, Cheverst et al. (2005) found that although users prefer transparency, they do not necessarily benefit from it. Capelo and Dias (2009) conducted simulation experiments using an SBLE with two different interfaces, one (the less transparent) presenting a set of financial indicators, and the other (the more transparent) providing a balanced scorecard which specifies the critical variables and relations of the simulator model. The results did not indicate significant differences in learning and performance between those two treatments. The authors found, however, that subjects submitted to a third condition, which additionally involved drawing causal maps (and reflecting upon them), revealed better model comprehension and performance. Conversely, a study reported by Gary and Wood (2016) reveals that providing subjects with a balanced scorecard strategy map improves their mental models and task performance. Kopainsky and Alessi (2015) found that making the model structure transparent produced mixed outcomes. Although participants provided with the more transparent strategy demonstrated better understanding of the causal structure of the underlying model, their performance was equivalent to those in the less transparent condition. The results of the experiments conducted by Kopainsky et al. (2015) showed that combining model transparency with prior exploration strategy (i.e. allowing participants to previously explore the simulation model in practice mode) improves participants' comprehension of the simulation model. The results of the simulation experiment conducted by Capelo and Silva (2020) evidence that the model transparency combined with the exploratory guidance improve students' comprehension. However, the learning effect of using only the transparent condition is more limited. In order to facilitate comprehension of model complexity, Van Borkulo et al. (2012) and Elsawah et al. (2017) recommend an approach (model progression) in which the details and aspects of the simulation model are gradually revealed to students, allowing them to incrementally build their mental models. The studies conducted by Mulder et al. (2015) pointed out that model progression combined with worked examples promote inquiry learning. Pavlov et al. (2015) investigated the effects of including a structural debriefing protocol to help students learn about the causal structure of a black-box simulation. The aim of that approach was to turn an opaque simulator into a transparent one. In their study, the participants were

challenged to build a system dynamics model that portrays the causal structure underlying the simulator. The studies of Qudrat-Ullah (2007, 2014, 2020) and Capelo et al. (2021) revealed that engaging students in discussions or debriefings about the model structure and behaviour enhanced their mental models and task performance.

As evidenced by the literature mentioned, previous research has produced mixed or inconclusive results about the learning and performance benefits of transparent simulations. Particularly, some studies mentioned above also revealed that model transparency only benefits learning and performance when it is combined with other instructional strategies, such as causal diagramming (Capelo & Dias, 2009), model exploration (Capelo & Silva, 2020; Kopainsky et al., 2015), and model progression (Elsawah et al., 2017; Van Borkulo et al., 2012). Consequently, specific instructional support is required to facilitate and develop learner ability to infer behaviour from causal structure (provided by transparent simulations) in complex, dynamic systems (Davidsen and Spector, 2015).

2.3 Learning and performance goals in complex tasks

Goal setting, a theory of motivation in organizational psychology, states that setting specific and high goals leads to higher performance than when easy goals, no goals, or even general goals, namely ‘‘to do one’s best’’ are set (Locke & Latham, 1990, 2013). The assumption in 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 that helps focus attention and provides motivation towards learning; it also helps 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 paying attention to instructions, developing task strategies to attain the goals, and processing and integrating relevant knowledge (Yang et al., 2017).

At the same time, previous studies have shown that providing no specific goals at all could benefit learning in problem-solving tasks (Sweller et al., 2019). According to the cognitive load theory (CLT) (Sweller, 2020), learning is compromised when the total cognitive load exceeds the available working memory capacity. That goal-free effect, which is derived from CLT, states that learning and performance will improve by setting vague goals, thus avoiding any unnecessary load that could result from setting distant, specific goals (Sweller et al., 2019). Such cognitive costs may generate distraction and deteriorate students' learning and performance outcomes (Crouzevialle & Butera, 2017). Gary et al. (2017) conducted laboratory experiments employing a business simulation to investigate the effects that adopting stretch goals could have on performance. The authors found no main effect of stretch goals on performance and concluded that stretch goals (compared with moderate goals) generate large attainment discrepancies that increase a propensity to take risks, undermine goal commitment, and generate lower risk-adjusted performance. Goal-setting theory distinguishes 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. While performance goals may lead to a situation in which students only attempt to reach their goals without actually acquiring the knowledge and skills needed. Whereas learning goals may lead to more learning-oriented behaviour such as focusing attention on mastering a task, discovering task-relevant strategies, and achieving learning objectives (Seijts & Latham, 2005). Nebel et al. (2017) conducted a study to compare different goal types (specific learning goal, specific performance goal, goal-free condition) within an educational video game. The results 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 have revealed that when there is a highly 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, when the requisite knowledge needs to be acquired, the approach proposed consists of assigning learning goals first, and then only assigning

performance goals once the students have learnt enough about the task (Chen & Latham, 2014; Latham et al., 2008; Latham & Seijts, 2016; Locke & Latham, 2013; Masuda et al., 2015; Seijts & Latham, 2005; Yang et al., 2017). The implicit assumption is that this learning phase helps individuals develop a deeper comprehension of the task and identify effective strategies, thus improving performance in a later stage when they are assigned challenging performance goals (Yang et al., 2018). Furthermore, some studies suggest that more challenging learning goals lead to higher performance than easier learning goals do (Latham et al., 2008; Locke & Latham, 2013; Latham & Seijts, 2016; Seijts and Latham, 2001; Yang et al., 2018).

On the other hand, a preponderant motivational mindset of performance orientation, which refers to an approach that focuses exclusively on increasing performance against external criteria (Birney et al., 2018; Seijts et al., 2004), may hinder learning and ultimately performance (e.g. Heslin, Latham, & VandeWalle, 2005). Setting learning goals may influence participants to adopt a mastery orientation mindset (which refers to a preference for goals that focus on learning and developing skills), which has been positively linked with self-regulation, learning, and consequently performance (e.g., Middleton & Midgley, 1997).

2.4 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; that is to say that 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 the instructional method be integrated with 'cognitive tools' aimed at guiding and supporting students' activities. Moreover, according to Davidsen and Spector (2015), the ability to infer behaviour from structure in complex, dynamic systems is a very advanced skill. As such, appropriate instructional guidance is required to promote effective learning of complex systems. In order to facilitate comprehension of model complexity, some researchers (Elsawah et al., 2017; Mulder et al., 2015; Van Borkulo et al., 2012) recommend an approach (model progression) in which the details and aspects of the simulation model are gradually revealed to students. Through that approach, learners will be able to gradually reason about the model structure, allowing them to incrementally build their mental models and improve their understanding of the simulated system. Moon and Brockway (2019) propose a guidance method that segments a complex task into simpler subtasks to reduce the level of cognitive load. Kopainsky et al. (2015) found that combining model transparency with prior exploration strategy (i.e. allowing participants to previously explore the simulation model in practice mode) improves participants' comprehension of the simulation model. The results of the experiment conducted by Capelo and Silva (2020) indicated the positive learning effects of using transparent simulations and exploratory guidance involving model progression, worked examples, and task segmentation. The researchers concluded that model transparency combined with exploratory guidance help students to both identify the model structure and comprehend the relationship between structure and behaviour. Debriefing sessions held between simulation runs may also be incorporated in the instructional method. These would take the form of discussions with the students about any difficulties they had related to comprehending the model structure and behaviour. 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., 2021; Dittrich et al.,

2022; Qudrat-Ullah, 2014, 2020). More recently, Obaid et al. (2023) suggest that the sequential patterns of learner actions may influence the outcomes of simulation-based guided discovery learning.

3. RESEARCH HYPOTHESES

The present study aims to investigate the effects that exploratory guidance, learning goals, and performance goals can have on the learning potential of transparent simulations in a dynamically complex task which, in this case, consists of starting and growing a business venture.

The expected relations and hypotheses are based on the following variables:

LPG - Level of Performance Goals. This variable indicates to what extent the instructional method includes the setting of specific, high performance goals.

LLGEG - Level of Learning Goals and Exploratory Guidance. This variable indicates to what extent the instructional method includes the setting of specific, high learning goals, worked under exploratory guidance.

From a model-based learning perspective (Landriscina, 2013), the learning 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. Throughout the simulation task, the students repeatedly appreciate the situation, mentally simulate the consequences of selected actions, and then define and implement courses of action which reflect their comprehension of the structure and behaviour of the simulator model.

CMD - Comprehension of model dynamics. This variable reflects how students comprehend the structure of the simulation model and to what extent they are able to infer its dynamic behaviour.

Performance. The performance of this simulation task is measured in terms of the financial value created by the venture.

In order to succeed in a transparent simulation of a complex task, students need to call upon considerable cognitive resources to interpret model diagrams, identify and comprehend the critical variables and relationships, infer model dynamics, and discover and implement

effective task strategies. As articulated in the literature review section, previous research has suggested that setting challenging performance goals can improve task performance (e.g. Locke & Latham, 1990, 2013; Nebel et al., 2017). The promise is that more challenging goals can stimulate greater cognitive effort to search for and develop effective task strategies to attain the goals. Consequently, setting higher performance goals may act as external stimuli, motivating students to engage the necessary cognitive resources during the simulation activities in order to take full advantage of the model transparency, which leads to hypotheses H1a and H1b:

H1a: The level of performance goals (LPG) positively influences the level of comprehension of the model dynamics (CMD) in a transparent simulation of a dynamically complex task.

H1b: The level of performance goals (LPG) positively influences the Performance in a transparent simulation of a dynamically complex task.

As previously mentioned in the literature review section, prior studies have evidenced that when the requisite knowledge needs to be acquired, learning and performance may benefit from assigning learning goals first and only assign performance goals once the students have learnt enough about the task (Chen & Latham, 2014; Latham et al., 2008; Seijts & Latham, 2005; Yang et al., 2017). Additionally, the literature suggests that more challenging learning goals lead to higher performance than easier learning goals do (Latham et al., 2008; Seijts and Latham, 2001; Yang et al., 2017; Yang et al. 2018). Prior research has also revealed that individuals improve learning and performance when they are subjected to exploratory guidance (e.g. Alfieri et al. 2011; Capelo & Silva, 2020; Clement, 2008; Kopainsky et al., 2015; Mayer, 2004). In this instructional strategy, learning goals are presented and then the students are free to explore the learning environment. The promise is that this type of guidance promotes inquiry-based learning, discovery learning (Alfieri et al. 2011; Mayer, 2004), and scientific reasoning (Clement, 2008). Students have the opportunity to iteratively formulate strategies, act, appreciate the consequences of their decisions, reflect, and test their comprehension of the cause-effect relations and dynamics involved in the simulation task (Capelo & Silva, 2020; Kopainsky et al., 2015). These arguments lead to hypotheses H2a and H2b:

H2a: The level of learning goals and exploratory guidance (LLGEG) positively moderates the effect of the level of performance goals (LPG) on the comprehension of the model dynamics (CMD) in a transparent simulation of a dynamically complex task.
H2b: The level of learning goals and exploratory guidance (LLGEG) positively moderates the effect of the level of performance goals (LPG) on the Performance of the simulation task in a transparent simulation of a dynamically complex task.

4. METHOD

4.1 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, 2017; Capelo et al., 2018; 2020; 2021). Many SBMEs for educational and research purposes have been developed with systems dynamics (SD) (Alessi & Kopainsky, 2015). We considered SD (as well as the software packages incorporating this approach) to be appropriate for developing the SBLE used to address our research problem because it provides stock-and-flow diagrams (SFDs) and other transparency features. The purpose of this SBLE is to illustrate concepts associated with the process of managing the growth of a business venture (Capelo et al., 2021). By interacting with this simulator, students would be able to appreciate the dynamic complexity involved in a business venture and any negative performance effects that may occur due to 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 screens present the historical behaviour of key variables over time. 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 (included in an MSc program in business management) with 68 students in total. Groups CG (with 22 students), E1 (with 24 students), and E2 (with 22 students). All the students have Portuguese nationality. One of the authors acted as instructor in these classes. Participants did not know the business game and had no previous experience with the simulator. The simulation task was performed individually in class. All participants were given a full experiment guide with instructions for interpreting CLDs and SFDs, case text, description and objective of the simulation task, and instructions for interacting with the simulator. The decisions and simulator outcomes were automatically stored in a protected spreadsheet on each participant's computer.

To succeed in this task, participants needed to understand the dynamic complexity derived from the cause-and-effect relationships among critical model variables (which are shown in the CLD and SFDs included in the SBLE interface). Previous research has shown that such model complexity can negatively influence both the formation of adequate mental models and task performance (Diehl & Sterman, 1995; Ozgun & Barlas, 2015). Additionally, subjects need to be familiarized with systems dynamics and be able to read and interpret causal-loop-diagrams and stock-and-flow diagrams so that they can recognize and comprehend the behaviour of dynamic structures (Davidsen & Spector, 2015). In order to obviate these problems, model transparency is complemented with structural and behavioural debriefings (Capelo et al., 2020; 2021). 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.

Treatment		Experiment 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 – Experiment procedure

The experiment procedure involved two sessions and had the following steps (Figure 1). Session 1. a) The participants received a lecture on CLDs and SFDs, so that they were able to read and interpret the CLD and SFDs available in the SBLE interface.

Session 2. In this session, students performed the simulation task using three simulation runs (of approximately 20 to 25 minutes each). They read the description of the simulation task and the simulator instructions (b). The students, after performing the first simulation run (c), participated in a structural debriefing (d) (lasting approximately 35 minutes). The instructor began this debriefing session by describing the CLD and SFDs to the students in the form of step-by-step guided tours, gradually including the model variables and relations. Any doubts concerning the model variables and their relations were clarified. After performing the second simulation (e), the students participated in a behavioural debriefing (f) (lasting approximately 50 minutes) focused on the relation between the model structure, courses of action, and corresponding dynamic behaviour. The instructor first described the main challenge of this simulation task and then explained the reference modes for the critical variables, their relation to the model structure, and the corresponding desirable and “fear” scenarios. The instructor then moderated a debate on how certain model structures (included in the CLD and SFDs of the simulator model) can support sustainable growth. g) The students from experimental group E2 (given learning goals, exploratory guidance, and performance goals) were assigned some specific learning goals related to three different simulation phases of value creation: starting (years 1-4), growing

(years 5-7), and sustaining (years 8-10). 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 needed to. 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 had identified and written 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 (given performance goals) and E2 (given learning goals, exploratory guidance, and performance goals) were then 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.

4.2 Research variables and data treatment

This section summarises the use of the variables that were defined in the research model. The learning outcomes, model dynamics comprehension and performance were assessed and compared with benchmark values. This method has been applied in previous studies (e.g., Diehl & Sterman, 1995; Kopainsky et al., 2015).

Level of Performance Goals (LPG). This variable features two degrees. In the low degree (coded as -1), students performed the simulation task with a global, vague performance goal. Their aim was to maximize value creation. In the high degree (coded as +1), students had specific, high performance goals. The aim here was to achieve certain outcomes in terms of client acquisition and value creation for each simulation phase.

Level of Learning Goals and Exploratory Guidance (LLGEG). This variable features two degrees. In the low degree (coded as -1), students performed the simulation task without specific learning goals and they were not given exploratory guidance. In the high degree (coded as +1), the students were given specific, high learning goals, combined with exploratory guidance. They were free to explore the simulator, performing all the

simulation runs they needed to. This experiment condition is designed to promote discovery learning with appropriate aids. They were asked to identify and test strategies to address specific business challenges. The students reflected on each issue, formulated some hypotheses about model behaviour, and defined scenarios to test those hypotheses. They ran the simulator, interpreted the results, tested the hypotheses, and determined the cycle repeats.

Comprehension of the model dynamics (CMD). This variable indicates how well 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 dynamic structures of the simulation model. This variable is calculated as the average of four components that are rated on 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 on a continuous scale (from 0 to 1) against reference values of MVA.

5. 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 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 (given only high performance goals). On average, the participants from group E2 (given 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.

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	.117	-0.097	0.067	.157
E2-CG	0.105*	0.040	.012	0.167*	0.069	.021
E2-E1	0.176**	0.041	.000	0.264**	0.076	.001

*$p < .05$, **$p < .01$

The students from control group (CG) and those from the group E1 (given only high performance goals) were subject to equivalent guidance conditions. The difference between those treatment groups is that while students from the 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 result in the participants having better outcomes. Instead, high performance goals compared with vague performance goals increased the variance in CMD and performance. This means that participants from group E1, who received specific, high performance goals for each phase throughout the simulation task, did not, on average, 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 the necessary knowledge of 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, whose understanding is poor, may experience additional pressure and cognitive load as they monitor their progress. Perceiving a persistent and increasing distance from the desired performance level would further diminish their available, limited cognitive resources. These cognitive costs may generate distraction and deteriorate learning and performance outcomes, which would erode motivation and goal commitment. These findings are somewhat 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.

On the other hand, the difference between treatment groups E1 and E2 is that students from the latter group had previously received 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, $p = .012$; Performance mean difference = 0.167, $p = .021$). Consequently, the variable LLGEG seems to positively moderate the impact of LPG on CMD and Performance. Students given high performance goals demonstrated, on average, an increasing comprehension of the model dynamics and performed better if they addressed previously high learning goals through exploratory guidance. As students explored the simulator to resolve the challenges associated with the learning goals, they were engaged in an inquiry process and had the 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 3, regression analysis for CMD on the independent variables shows a low significant negative effect for LPG ($\beta = -.212$, $p = .095$) and no significant effects for LLGEG ($\beta = -.176$, $p = .174$). Regression analysis of

Performance shows strong significant positive effects for LPG (β = .529, $p < .001$) and LLGEG (β = .4792, $p < .001$).

Table 3 – Regression results for all independent variables

Independent Variables	Dependent Variables			
	CMD - Comprehension of Model Dynamics		Performance	
	Standardised Beta	*p*-value	Standardised Beta	*p*-value
LPG - Level of Performance Goals	-.212*	.095	-.176	.174
LLGEG - Level of Learning Goals and Exploratory Guidance	.529**	.000	.479**	.000
Adjusted R^2	.194		.154	

*p< .1, **p< .01

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.

These results confirm two of the four hypotheses. As indicated in 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 .05 significance level) of LPG on CMD and Performance. In contrast, regression for CMD reveals a low significant negative effect for LPG (at .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 performance in a transparent simulation of a dynamically complex task. 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 performance in a transparent simulation of a dynamically complex task.

6. CONCLUSION

This study is based on an educational experiment aimed at testing hypotheses about the effects that setting learning and performance goals have 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 confirm two of the four hypotheses. Hypotheses H1a/b (the level of performance goals positively influences the comprehension of the model dynamics and performance in a transparent simulation of a dynamically complex task) are not supported. In the present experiment, students needed to apply considerable cognitive effort to interpret and reflect on the information provided by the transparent interface in order to comprehend the model dynamics and discover effective task strategies. The findings indicate that setting specific, high performance goals did not benefit that process. These results seem to confirm the proposition articulated in previous research that providing no challenging goals could benefit learning in complex tasks (Crouzevialle & Butera, 2017; Gary et al., 2017; Sweller et al., 2019). 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 (Sweller, 2020), 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 to deal with the extra information provided by the transparent condition.

By previously working specific, high learning goals, under exploratory guidance, students significantly improved comprehension and task performance, supporting 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 performance in a transparent simulation of a dynamically complex task). 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 on and learn 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 what previous research states about the effects of goal setting on performance in highly complex tasks (e.g. Chen & Latham, 2014; Latham et al., 2008; Latham & Seijts, 2016; Locke & Latham, 2013; Seijts & Latham, 2005; Yang et al., 2017; Yang et al., 2018); which is that in situations where the primary requisite is acquisition of knowledge and skills, a specific learning goal that is challenging rather than an outcome goal should be set. With regard to the effect of exploratory guidance, these results are also consistent with the studies of Kopainsky et al. (2015) and Capelo and Silva (2020). As reported by those authors, we also found that students achieve a deeper understanding of the model dynamics when they have the opportunity to explore the simulation themselves while receiving appropriate guidance and facilitation.

6.1 Contributions

While model transparency has been accepted as an important condition for developing effective comprehension of the task complexity (Größler et al., 2000; Groesser, 2012; Landriscina, 2013; Milrad et al., 2003), the type of instructional strategies that optimize the learning potential of transparent simulations requires further examination. Previous research has examined different instructional strategies that can be applied in the context of transparent SBLEs (e.g. Capelo & Dias, 2009; Capelo & Silva, 2020; Capelo et al., 2021; Elsawah et al., 2017; Gary & Wood, 2016; Kopainsky et al., 2015; Mulder et al.; 2015; Qudrat-Ullah, 2007, 2014, 2020; Yang et al., 2017; Van Borkulo et al., 2012). The present study takes a further step by examining the effects of combining exploratory guidance,

learning goals, and performance goals in a transparent simulation of a dynamically complex system. The results suggest that exploratory guidance, learning goals (previously worked), and performance goals provide powerful learning mechanisms to apply in a transparent simulation of a dynamically complex task. Conversely, the learning and performance effects of using only performance goals are more limited. Learning goals, previously worked in earlier stages under exploratory guidance, seem to lead students to shift their attention from the end result to the process of comprehending the model dynamics and discovering successful task strategies. This further enhanced students' performance in the later stage of the simulation task when they were assigned high performance goals.

The results of this study strongly evidence that an SBLE for learning in complex and dynamic domains can benefit from an instructional strategy that combines model transparency with exploratory guidance, learning goals, and performance goals.

The outcomes of this experiment also contribute to advancing the area of system dynamics by re-emphasizing the relevance of using educational simulators, in conjunction with certain instructional methods, as a fundamental approach for improving performance and learning in complex and dynamic tasks.

Finally, the current study contributes to the ongoing research associated with the development of the goal-setting theory by reinforcing the assumption already articulated in previous studies. This is that, in complex tasks, when the requisite knowledge needs to be acquired, learning and performance benefit from assigning learning goals first, and only assigning performance goals once the individuals have learnt enough about the task (e.g Chen & Latham, 2014; Latham et al., 2008; Latham & Seijts, 2016; Locke & Latham, 2013; Seijts & Latham, 2005; Yang et al., 2017; Yang et al., 2018).

6.2 Limitations and future research

The students' comprehension of the model structure and dynamics was not measured directly in this experiment and could, therefore, be a matter for future research. Instead, the present study used the variable CMD which measured how students succeed in dealing with certain dynamical structures of the simulation model.

The present study analysed the combined effects of progressively adding performance goals, learning goals, and exploratory guidance in a transparent simulation of a dynamically complex system. Further research might consider a research design that would permit investigation of the individual impacts of these simulation conditions.

Additionally, there are several potential methodological limitations that affect the external validity of the present study. Although the difference in means (independent sample *t* test) and regressions passed the tests for their assumptions, including the Shapiro-Wilk and Lilliefors (modified Kolmogorov-Smirnov) tests for normality of data and regression residuals, the sample used is relatively small and limited to Portuguese graduate students enrolled only in a business school. Furthermore, the research method was based on a quasi-experimental design as there was no random allocation of students to the experimental and control groups. Each treatment group consisted of students from one class; otherwise, the participants would have different educational activities in the same classroom, which would have been difficult to control. Standardised student-instructor relationships and classroom features were also difficult to control. Despite these limitations that affect the generalizability of these findings, this study should be of interest to researchers in the field and the many educators who teach through SBLEs.

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DECLARATION OF INTEREST

The authors declare not having any financial and personal relationships with other people or organizations that could inappropriately influence (bias) this work.

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