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Expanding model transparency and learning potential through structural and behavioral
debriefings

Carlos Capelo

Universidade Europeia

Estrada da Correia, 53, 1500-210 Lisboa – Portugal

carlos.rosario@universidadeeuropeia.pt

corresponding author

Renato Pereira

Iscte Business School

Avenida das Forças Armadas, 1649-026 Lisboa – Portugal

renato.pereira@iscte-iul.pt

João Ferreira Dias

Independent researcher

R. Luis Pedroso de Barros, 26

1400-238 Lisboa – Portugal

joao.ferreira.dias@gmail.com

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Performance effects of structural and behavioural debriefings in transparent simulations.

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Abstract

Simulation-based learning environments have been recommended by researchers as educational tools to support learning in complex domains. However, studies have evidenced that subjects may nevertheless have great difficulty understanding and managing dynamic systems, with several assertions are being made regarding the impact of employing transparent model simulations on learning and performance outcomes. This research, therefore, examines the moderating impacts of structural and behavioral debriefings, which are concentrated respectively on critical variables and relations, and on the connection between model structure, action patterns, and system behavior. We propose a series of hypotheses regarding the impact of model transparency and prior debriefing conditions on participants' performance and their comprehension of the system dynamics. Three out of the six hypotheses were validated: prior structural debriefing alongside model transparency positively impacts performance; prior behavioral debriefing, when combined with model transparency and prior structural debriefing, positively impacts both the comprehension of model dynamics and performance.

Keywords

System dynamics, Simulation-based learning, Business simulation, Model transparency, Simulation debriefing.

Introduction

Simulation-based learning environments (SBLEs) have been recommended by researchers as educational tools to support learning in complex domains (Cunico et al., 2021; Davidsen & Spector, 2015; Groesser, 2012; Landriscina, 2013; Maier & Größler, 2000; Rouwette et al., 2004; Sterman, 1994). Through such tools, 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; Groesser, 2012; Sterman, 1994). However, a considerable number of studies based on simulation experiments have consistently indicated that subjects have difficulty correctly perceiving dynamic complexity (e.g.

Atkins et al., 2002; Cronin & Gonzalez, 2007; Diehl & Sterman, 1995; Hendijani, 2021; Kampmann & Sterman, 2014; Ozgun & Barlas, 2015; Sterman, 1989, 2002, 2010; Sterman & Dogan, 2015; Stouten & Größler, 2017; Strohhecker & Leyer, 2019).

Many SLBEs are of the opaque or black-box type where the structure of the simulation model is concealed from learners. Studies have suggested that simulations of opaque models can interfere with proper learning (Landriscina, 2013; Rouwette et al., 2004). 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 model simulations has been proposed to obviate the problem of developing misinterpretations of the model structure and behavior. 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 behavior of the simulated system (Groesser, 2012; Milrad et al., 2003).

Previous research has suggested that model transparency may only benefit learning and performance when it is combined with other instructional strategies (Capelo & Dias, 2009a; Capelo & Silva, 2020; Elsayah et al., 2017; Größler et al., 2000; Humphreys et al., 2016; Kopainsky & Alessi, 2015; Kopainsky et al., 2015; Machuca, 2000; Mulder et al., 2015; Qudrat-Ullah, 2007; Van Borkulo et al., 2012), such as when debriefing sessions are incorporated (Crookall, 2010; Kriz, 2010). This invites the research question - what type of instructional support needs to be offered in order for learners to be able to take full advantage of transparent model simulations? Therefore, in order to open the way for the necessary deepening of this research, the present study aims to contribute to the effectiveness of SBLEs by investigating the moderating effects of an approach consisting of the systematic application of structural and behavioral debriefing throughout the simulation rounds, as far as the impact of model transparency on learning and performance in a complex dynamic task is concerned.

Dynamic Complexity, Double Loop Learning, and Simulation-Based Learning

As emphasized by Forrester (1961), the real world is dynamically complex, involving the multi-loop, multi-state and non-linear nature of the feedback systems in which we live. Sterman (2000) explains that most people think in terms of detailed complexity,

which relates to the number of components in a system or the number of combinations to consider when making decisions. Dynamic complexity, on the other hand, can arise, even in simple systems, from the interactions between agents over time, in such a way that the system produces outputs that are not easily predictable (Ozgun & Barlas, 2015). Social systems exhibit potentially significant levels of dynamic complexity. As articulated by Sterman (1994), each agent's decisions represent only one of numerous feedback loops functioning within a given system; these loops can embody both expected and unexpected side effects of the decision maker's actions. There can be both positive and negative feedback loops, and these loops will encompass numerous stocks (state variables) and a multitude of nonlinearities.

A significant body of research based on simulation experiments has revealed that subjects have difficulty perceiving dynamic complexity correctly since biases and perception errors may occur (e.g. Atkins et al., 2002; Cronin & Gonzalez, 2007; Diehl & Sterman, 1995; Hendijani, 2021; Kampmann & Sterman, 2014; Ozgun & Barlas, 2015; Sterman, 1989, 2002, 2010; Sterman & Dogan, 2015; Stouten & Größler, 2017; Strohhecker & Leyer, 2019). According to Sterman (2002), people tend to have difficulty correctly understanding the basic principles or building blocks of dynamical systems, such as feedback loops, stocks and flows, and system delays. The dynamics of a system is determined by the interaction between those building blocks, which make up its endogenous structure. Feedback loops are cognitively challenging to the human mind because they imply circular reasoning (e.g. Diehl & Sterman, 1995; Kampmann & Sterman, 2014). Subjects also tend to misperceive the effects of accumulation processes involved in the interaction between stocks and flows in the system (e.g. Cronin & Gonzalez, 2007; Hendijani, 2021; Sterman, 2010; Stouten & Größler, 2016; Strohhecker & Leyer, 2019). Some empirical studies also indicate that subjects have difficulties in recognizing and addressing system delays (e.g. Ozgun & Barlas, 2015; Sterman & Dogan, 2015).

This research is based on the concepts of double loop learning and mental models (Argyris & Schon, 1974; Capelo & Dias, 2009b; Davidsen & Spector, 2015; Doyle & Ford, 1998, 1999; Gary & Wood, 2011; 2016; Richardson et al., 1994; Schaffernicht, 2019; Scott et al., 2014; Sterman, 1994). The theory of double loop learning, developed by Chris Argyris and Donald Schon in the seventies (Argyris & Schon, 1974), is based

on the detection and correction of errors through two different feedback loops. This involves governing variables that translate the mindset of the situation, as well as the actions taken to change the system and the results of those actions. In single-loop learning, individuals assess achieved outcomes against intended outcomes and, without challenging their mental models and objectives, take actions they perceive will progress the system toward the desired condition. In double-loop learning, individuals use feedback information to reflect on the causal chain of a problem, questioning and eventually adjusting their mindset and goals of the situation.

The concept of mental models can be defined as internal and simplified representations of the reality, and are used to describe and explain real-world behavior, as well as to guide learning and decision-making processes. In system dynamics literature, the definition of the concept of mental models has evolved. Forrester (1961) affirms that an abstract representation or a textual depiction in English can constitute a framework of corporate structure and its operational procedures. Managers consistently engage with these conceptual and linguistic frameworks of the organization. These representations do not embody the actual corporation. They may not always be accurate. Instead, they serve as constructs in our cognition to stand in for the genuine system they portray...

The conceptual depiction of the external environment that individuals maintain mentally is a model. One does not mentally contain a city, government, or country. Rather, one holds selected ideas and interconnections that are employed to depict the genuine system. Sterman (1994, 2000) argues that within system dynamics, the concept of mental model encompasses our perceptions regarding the interconnected causal relationships that delineate the operational behavior of a system. This includes specifying the model's boundaries (incorporated and excluded variables) and determining the pertinent time horizon for problem framing or articulation. Doyle and Ford (1998, 1999) characterize a cognitive schema of a dynamic system as a relatively persistent and easily retrievable, yet constrained, internal conceptual depiction of an external system (past, current, or anticipated) whose configuration mirrors the perceived arrangement of that system. In a more recent context, Groesser and Schaffernicht (2012) expand upon the aforementioned definition by detailing that the internal depiction comprises, at a conceptual level, feedback loops that strengthen and stabilize. These loops are composed of interrelated stocks, flows, and intermediary variables, with

causal connections that may be positive or negative, linear or non-linear, and potentially subject to delays.

A central feature of mental models is that they reproduce individuals' beliefs about cause-and-effect relationships (Sterman, 1994). However, subjects' mental models are not identical to external realities; they are often incomplete and sometimes flawed models of the real system that is being represented (Doyle & Ford, 1998). Moreover, due to inherent human cognitive constraints, the cognitive frameworks that decision makers construct and employ inevitably exhibit imperfections (Sterman, 1994). A mental model that contains incorrect or inaccurate assumptions implies that there are significant differences between the decision maker's understanding and the business reality (Capelo & Dias, 2009a, 2009b; Gary & Wood, 2011, 2016; Sterman, 1989). Thus, it is reasonable to assume that, by enhancing their mental models, decision-makers should be able to improve their capacity to comprehend and deal with dynamically complex relationships. In this framework, Sterman (1994) underscores the significance of offering opportunities for double-loop learning, where system information is utilized not solely for decision-making within established frameworks, but also loops back to adjust subjects' mental models, thereby fostering the development of novel strategies and policies.

The aforementioned difficulties in understanding dynamic complexity have been attributed to incomplete and inaccurate mental models (e.g. Diehl & Sterman, 1995; 1993; Sterman, 1989, 1994). Previous research on mental models of dynamical systems has specified two types of deficiencies related to feedback misperceptions: i) misperceptions of the system structure that occur because the causal relationships of complex decision contexts are difficult to identify and accommodate within subjects' mental models (e.g. Capelo & Dias, 2009b; Sterman, 1989) and ii) misperceptions of system dynamics that arise because decision-makers, when trying to anticipate the consequences of their actions, have difficulty accurately inferring behavior that emerges from delays and feedback structures (e.g. Capelo & Dias, 2009b; Diehl & Sterman, 1995; Sterman, 1989). Richardson et al. (1994) conceived two logics regarding the mental models that decision-makers may employ to learn and succeed as they interact with systems: design logic, which focused on improving decision-makers' mental models of system causal structure, and operator logic, which is based on selecting

strategies and tactics for accomplishing their goals. The findings by Richardson et al. (1994) suggest that conditions that influence the design logic level, but fail at the operator logic level, will not significantly affect performance. Nevertheless, prior research has asserted that, in complex problem-solving situations, the accuracy of mental models of system causal relationships is a predictor of learning and performance (Capelo & Dias, 2009a, 2009b; Gary & Wood, 2011, 2016).

Simulation-based learning environments (SBLEs) have been recommended by researchers as educational tools to support learning in complex domains (Cunico et al., 2021; Davidsen & Spector, 2015; Groesser, 2012; Landriscina, 2013; Maier & Größler, 2000; Rouwette et al., 2004; Sterman, 1994). As mentioned by Groesser (2012), model-based learning refers to the interaction of subjects with an external, formal simulation model for learning purposes. Broadly speaking, SBLEs for learning purposes contain more than a computer model as they comprise virtually everything connected with the learning process, such as case descriptions, presentations by a facilitator, background information, and working instructions (Davidsen & Spector 1997). As asserted by Landriscina (2013), SBLEs include four layers corresponding to: (1) the computational model, (2) the user interface that allows students to observe the simulated phenomena and to interact with the computational model, (3) the instructional support (for example: questions, exercises, exploration guides, and concept maps), and (4) the complementary activities conducted by students. As stated by 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). In accordance with the theory of double loop learning, system information is utilized not only for decision-making within current frameworks but also loops back to adjust the mental models of individuals (Sterman, 1994). Therefore, viewed through the lens of double loop learning, students can utilize an SBLE to facilitate the development and refinement of their mental models. Students develop model-based reasoning as they form an initial mental model of the problem situation, predict its evolution on the basis of mental simulation, compare it to the simulation results, and successively change and improve their mental model of the situation (Landriscina, 2013). The assumption here is that learners, in an SBLE, must create an

adequate mental model to support effective decision-making. If students' mental models are not similar to the underlying model, their comprehension and performance in the SBLE will suffer.

Model Transparency

In the present study, simulator model transparency refers to the ability of the SBLE to enable students to identify and comprehend the critical assumptions, variables, and relationships that mainly determine the behavior of the simulated system. Transparent Synchronous Blended Learning Environments (SBLEs) allow students to visually represent the variables and relationships incorporated within the model through diagrams featuring nodes and interconnected links (Landriscina, 2013). Many SBLEs are of the opaque type, which means that the structure of the computational model is not revealed to users. Studies have suggested that this type of black-box situation could lead students to build inaccurate mental models, and thus interfere with proper learning (Landriscina, 2013; Rouwette et al., 2004). In an opaque model simulation, learners tend to automatically define and attribute rules to the system. As learning evolves through a process of trial and error, the students base their decisions on those rules. While these rules may match those included in the model, they might also be wrong or incomplete, thus leading to faulty learning (Machuca, 2000). Simulations with transparent models have been recommended in the literature to mitigate the problem of developing incorrect understandings of the models, which can hinder learning. In transparent SBLEs, students are able to access the critical variables and relations that mainly explain the model behavior. This approach may help learners to better understand the relationship between the structure and behavior 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 causal loop diagrams (CLDs) and stock-and-flow diagrams (SFDs) which make the relations between the model variables visible (Lane, 2008). However, according to Davidsen and Spector (2015), in order to take advantage of the transparency of SD models, students must be able to interpret a stock-and-flow diagram, once this representation is used to visualize the model structure.

The results of previous studies are ambiguous as to whether transparency moderates learning (Capelo & Dias, 2009a; Capelo & Silva, 2020; Elsayah et al., 2017; Gary & Wood, 2016; Größler et al., 2000; Humphreys et al., 2016; Kopainsky & Alessi, 2015; Kopainsky et al., 2015; Machuca, 2000; Mulder et al., 2015; Qudrat-Ullah, 2007; Van Borkulo et al., 2012). Machuca (2000) found that transparent model simulations favor management learning of organizational 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. On the other hand, the study by Cheverst et al. (2005) showed that although the participants were in favor of transparency, they did not take advantage of it. The study of Qudrat-Ullah (2007) revealed that engaging students in pre-discussions about the model structure enhanced their mental models and task performance. Capelo and Dias (2009a) 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) and the study conducted by Humphreys et al. (2016) reveal that providing subjects with a balanced scorecard strategy map improves their mental models and task performance. Kopainsky and Alessi (2015) observed that enhancing the transparency of the model's structure resulted in varied outcomes. While participants exposed to the more transparent approach exhibited improved comprehension of the causal structure of the underlying model, their overall performance remained comparable to those in the less transparent condition. The results of the experiment 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. In order to facilitate comprehension of model complexity, 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, allowing them to incrementally build their mental models. El Sawah et al. (2017) observed beneficial educational outcomes from model advancement. In their research, subjects engaged with a system dynamics model illustrating a water resource management framework. As participants progressed through the simulation, additional variables and relationships were revealed. That approach allowed participants to reason about the model structure incrementally, improving their understanding of the simulator. 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 model 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. Capelo and Silva (2020) conducted educational experiments to explore the effects of using model transparency and exploratory guidance. The results provide evidence that the model transparency combined with the exploratory guidance help students to improve their comprehension of both model structure and behavior. However, the learning effect of using only the transparent condition is more limited. The authors concluded that participants must both identify the model structure and comprehend the relationship between structure and behavior.

As articulated above, the literature reveals simulation approaches with varying degrees of model transparency. From (i) a simple approach consisting of providing information about the variables and relations in the form of balanced scorecard strategy maps (e.g. Capelo & Dias, 2009a; Gary & Wood, 2016; Humphreys et al., 2016) to more advanced methods such as (in no particular order): (ii) providing and/or incorporating representations of the structure of the simulation model through causal loop diagrams and/or stock-and-flow diagrams (e.g. Größler et al., 2000; Machuca, 2000); (iii) embedding the output graphs in causal loop diagrams or stock-and-flow diagrams that show the student both the structure of the model and the behavior (e.g. Capelo et al., 2021; Kopainsky & Alessi, 2015); complementing graphical information about the model structure with (iv) drawing causal maps and reflecting upon them (e.g. Capelo &

Dias, 2009a), (v) engaging students in pre-discussions about the model structure (e.g. Qudrat-Ullah, 2007), or (vi) allowing participants to explore the simulation model (e.g. Capelo & Silva, 2020; Kopainsky et al., 2015); and (vii) gradually revealing to students the structure and behavior of simulation model (model progression) (e.g. Borkulo et al., 2012; Elsayah et al., 2017).

As evidenced by the mentioned literature, previous research has suggested that model transparency (through the provision of structural information) may only benefit learning and performance when it is combined with other instructional strategies, such as causal diagramming (Capelo & Dias, 2009a), model exploration (Capelo & Silva, 2020; Kopainsky et al., 2015), and model progression (Elsawah et al., 2017; Van Borkulo et al., 2012). Previous research seems to suggest that students must not only access and identify the structure of the simulator model but also have to recognize the relationship between structure and behavior. Consequently, specific instructional support is required to facilitate and develop learner ability to infer behavior from causal structure (provided by transparent model simulations) in complex, dynamic systems (Davidsen and Spector, 2015).

Simulation Debriefing

According to many scholars, debriefing is a critical step in any SBLE (Crookall, 2010; Kriz, 2010). A debriefing session is a specific type of feedback process, wherein the students are systematically guided and encouraged to reflect on their learning experiences through a structured set of questions, hints, and explanations (Fanning & Gaba, 2007). During these sessions, conducted either post-simulation rounds or during intervals between them, students can address task challenges and seek clarification on their understanding of model variables, relationships, and associated behaviors. This method can also improve students' motivation and commitment to the simulation task, leading to better learning and performance outcomes. In particular, this method can be determinant in helping students enhance their mental models and thus resolve any misconceptions about dynamic and complex tasks (Pavlov et al. 2015; Qudrat-Ullah 2007, 2014, 2020). The assumption, therefore, is that debriefing may increase the learning potential of SBLEs, particularly those involving complex and dynamic tasks.

A central issue, however, consists of selecting the type of content that should be included in a debriefing session in order to help learners overcome their difficulties regarding dynamical complexity. Prior research has shown that the type of information feedback associated with dynamic decision-making environments can affect performance (e.g. Atkins et al., 2002; Diehl & Sterman, 1995; Franco et al., 2021; Gary & Wood, 2016, Hsiao & Richardson, 1999; Qudrat-Ullah, 2020; Richardson et al., 1994; Sengupta & Abdel-Hamid, 1993; Sterman, 1989). The two types of difficulties learners encounter that have been consistently reported in relation to system dynamics misperceptions are i) misperceptions of the system structure that occur because the causal relationships are difficult to identify and ii) misperceptions of system dynamics that arise because decision-makers have difficulty accurately inferring behavior that emerges from delays and feedback structures (e.g. Capelo & Dias, 2009b; Diehl & Sterman, 1995; Sterman, 1989). Consequently, debriefing sessions should address both of those dimensions: i) model causal structure and ii) the relation between structure and system behavior. Richardson et al. (1994) suggest that feedback information should follow both the design logic (focused on improving decision-makers' mental models of the system causal structure) and the operator logic (based on selecting strategies and tactics for accomplishing their goals). Similarly, Franco et al. (2021) and Sengupta & Abdel-Hamid (1993) state that subjects provided with cognitive feedback (information about existing relations within the environment) and with feedforward (recipes or rules of thumb for acting in the environment) tend to perform better than those that only receive outcome feedback (information about the state of the environment after strategy implementation). Qudrat-Ullah (2020) defines two ways to organize debriefing discussions: outcome-oriented debriefing (where participants are asked to recall, reflect, and compare their own solutions with a benchmark solution) and process-oriented debriefing (where participants are led through a process that illustrates the underlying structure of the task system and how it relates to the behavior of the task system). According to the author, outcome-oriented debriefing may not be enough to help learners overcome the misperceptions about the dynamic task. The study conducted by Atkins et al. (2002) suggests that the graphical format (rather than the tabular format) for presenting information in debriefing sessions favors learning.

Prior research has explored the influence of debriefing on learning outcomes and task performance in simulated environments (Capelo et al., 2020, 2021; Pavlov et al., 2015; Qudrat-Ullah, 2014, 2020). Pavlov et al. (2015) hypothesized that following a structured debriefing protocol would enhance students' comprehension of simulator architecture. Nonetheless, the authors noted that implementing this protocol necessitated a significant time investment. Qudrat-Ullah (2014) conducted simulation experiments that involved pre-task, in-task, and post-task facilitation sessions where critical aspects of the task were discussed. Those discussions were designed to improve participants' understanding of the structure and behavior of the simulation model. His findings indicated that the sessions generally improved students' mental models and task performance. However, when only the pre-task session was applied, the participants performed poorly. More recently, Qudrat-Ullah (2020) reported a simulation experiment in which participants managed a dynamic task. Two experimental groups were subjected to an outcome-oriented debriefing (where participants are guided towards reflecting and comparing their strategies with a reference strategy) and a process-oriented debriefing (where participants are shown the underlying structure of the simulator model and how it relates to the behavior of the model). The author found that process-oriented debriefing improved the task performance of those participants and helped them gain task knowledge. The simulation experiment conducted by the Capelo et al. (2021) revealed that participants submitted to a given treatment condition that involved debriefing sessions outperformed those from the control group. The present article expands and deepens the analysis of the study previously reported by Capelo et al. (2020).

Hypotheses

The current research endeavors to investigate how simulation debriefing moderates the influence of model transparency on learning outcomes and performance in a complex, dynamic task. The phrase "previous debriefing" as defined in the hypotheses refers to the application of debriefing sessions in prior simulation rounds.

Previous studies have suggested that model transparency is beneficial and should be incorporated in complex SBLEs (Capelo & Silva, 2020; Elsayah et al., 2017; Gary & Wood, 2016; Größler et al., 2000; Kopainsky & Alessi, 2015; Machuca, 2000; Mulder

et al.; 2015; Pavlov et al., 2015; Qudrat-Ullah, 2007; Van Borkulo et al., 2012).

Consequently, the current research posits that if students can effectively utilize and analyze graphical representations (integrated within the simulator interface) depicting the model's framework, they will likely develop more accurate cognitive frameworks. This enhancement is expected to result in improved performance on simulation tasks, supporting the formulation of the first and second hypotheses:

Hypothesis 1 - the degree of transparency positively influences understanding of the model dynamics;

Hypothesis 2 - the degree of transparency positively influences performance.

Past research has established that debriefing sessions can enhance simulation-based learning (Crookall, 2010; Kriz, 2010; Fanning & Gaba, 2007). Certain research has demonstrated that involving participants in preliminary activities aimed at enhancing comprehension of the model framework (such as dialogues, demonstrations, and model investigation) could enhance the efficacy of simulations (Größler et al., 2000; Kopainsky & Alessi, 2015; Kopainsky & Sawicka, 2011; Qudrat-Ullah, 2007, 2014, 2020). In line with these findings, the present study assumes that combining the transparent model simulation with a previous structural debriefing session gives the instructor an opportunity to elaborate on the critical variables and relations that are visible to participants. The information and support provided are consistent with the design logic (focused on improving decision-makers' mental models of the system causal structure) and the cognitive feedback (information about existing relations within the environment) proposed respectively by Richardson et al. (1994) and Sengupta and Abdel-Hamid (1993). Consequently, the anticipation is that structural debriefing combined with model transparency will have a beneficial impact on model understanding and efficacy, thereby supporting the third and fourth hypotheses. As structural debriefing complements model transparency, the hypotheses can be equivalently stated in terms of moderation effects.

Hypothesis 3: Prior exposure to structural debriefing combined with model transparency enhances comprehension of the model dynamics. Structural debriefing effectively moderates the influence of transparency levels on understanding model dynamics.

Hypothesis 4: Prior exposure to structural debriefing combined with model transparency has a beneficial effect on performance. As well documented in the literature, subjects

have difficulty understanding and managing complex dynamic systems (e.g. Diehl & Sterman, 1995; Kampmann & Sterman, 2014; Sterman, 1989; Sterman & Dogan, 2015). A specific cognitive challenge commonly discussed in the field of system dynamics (Davidsen & Spector, 2015; Schaffernicht, 2010) centers on the comprehension of emergent behavior in complex systems arising from their fundamental causal framework, often linked to inadequacies in dynamic mental models (Sterman, 1994). Prior research has indicated that post-experiment discussions can assist participants in clarifying misunderstandings regarding the dynamics of intricate systems (Pavlov et al. 2015; Qudrat-Ullah 2007, 2014, 2020). Accordingly, the present study assumes that complementing model transparency and previous structural debriefing with a previous behavioral debriefing session gives the instructor an opportunity to elaborate on the relation between model structure, patterns of action, system behavior, and performance. The content of this debriefing is congruent with the process-oriented type proposed by Qudrat-Ullah (2020), where participants are led through a process that illustrates the underlying structure of the task system and how it relates to the behavior of the task system. This type of debriefing allows students to address the gaps between their expectations of model behavior and its actual behavior and task performance. As a result, the students will benefit from a more effective understanding of the structure and behavior of the simulation model, and thus they will acquire a sharper perception of the impact of their actions and perform better in the simulation task. These debriefing sessions also involve discussions about the patterns of actions that lead to the success of the simulation task. As such, this type of debriefing includes elements that are consistent with the operator logic (based on selecting strategies and tactics for accomplishing their goals) and feedforward (recipes or rules of thumb for acting in the environment) proposed respectively by Richardson et al. (1994) and Sengupta and Abdel-Hamid (1993).

Therefore, it is anticipated that prior behavioral debriefing, in conjunction with model transparency and preceding structural debriefing, will have a constructive impact on both the comprehension and operational effectiveness of model dynamics, thereby supporting the fifth and sixth hypotheses. In the present approach, behavioral debriefing is applied as a complementary method. Thus, these hypotheses can also be written in terms of moderation effects.

Hypothesis 5: Prior behavioral post-examination, when combined with model transparency and previous structural post-examination, enhances comprehension of model dynamics.

Hypothesis 6: Prior behavioral debriefing, when combined with model transparency and preceding structural debriefing, enhances performance.

Method

Simulator Overview

System dynamics (SD) has been applied to building SBLEs for educational and research purposes (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 simulation model on which this SBLE is based has been developed and used in previous studies (Capelo et al., 2018, 2020, 2021).

This SBLE was specially developed to illustrate some system dynamics concepts associated with the process of managing the growth of a business venture (Capelo et al., 2021). These concepts include feedback loops, delays, and accumulation processes, which are covered in a course on entrepreneurship as part of a Master of Science in Management. Through this SBLE, the students will be able to appreciate the dynamic complexity involved in a business venture and any negative performance effects that may occur due to system misunderstanding. In particular, the simulator features the feedback mechanism of word-of-mouth (WOM) and its effect on building a customer base, as well as the concept of the customer choice pipeline to represent the process of developing potential customers as they gradually become aware, interested, and full adopters of innovative products.

The simulator represents the dynamics of the development of an ESCO (energy service company) venture. An ESCO designs, implements, and operates energy performance contracting (EPC) projects. Energy projects based on EPC consist of the implementation of measures that improve energy efficiency or enable facilities to generate renewable energy. EPC is an agreement between the facility user or owner and the ESCO, under which the ESCO designs and implements a green energy project,

finances that investment, and uses the revenue stream from the energy savings or renewable energy produced to repay the investment.

This SBLE includes two different interfaces, one with the conditions of an opaque model simulation and the other representing a transparent model simulation. The opaque interface consists of three screens: A control interface featuring essential performance metrics and input sliders for simulating decisions, accompanied by two screens showcasing historical trends of critical variables over time. Within the transparent interface, graphical representation is provided through a stock and flow diagram, illustrating both the model's specific structure and its corresponding dynamics to the student. Additionally, three screens present the Causal Loop Diagram (CLD) and selected Stock and Flow Diagrams (SFDs) of the simulator model. Figure 1 illustrates the causal loop diagram accessible to students via the clear interface, featuring reinforcing (R) and balancing (B) feedback loops that depict the dynamics of ESCO venture development (Capelo et al., 2018, 2020, 2021).

«Figure 1 is about here»

Figure 1. Causal loop diagram

The feedback loops in the CLD are described as follows (Capelo et al., 2021). R1 - As the first prospects implement EPC projects with the ESCO, they can interact with other prospects (WOM effect) and convince them to engage in EPC projects. B1 - Market saturation limits the growth of EPC adopters. The more EPC adopters, the fewer new potential clients. R2 - As more EPC contracts are won, the workforce required to capture these business opportunities increases, leading to workforce adjustment decisions. By hiring new employees, the company will be able to allocate additional resources to EPC business activities, and thus more potential customers will become EPC adopters. B2 - This balancing loop aims to adjust the number of employees in the company. B3 - Hiring new employees increases operating costs and negatively impacts financial performance. This balancing loop aims to adjust the desired workforce while taking into account any financial constraints. R3 - By gradually developing and perfecting its network of new partners, the company is able to increase its attraction of new EPC customers, increasing

the attractiveness of the firm to new potential partners. R4, R5 - These are virtuous cycles of learning and experience. As employees become involved in EPC projects, they gain more experience and improve their skills, thereby increasing their productivity in all ESCO activities. R6 - As the company improves its performance and increases the value created by its operations, shareholders will begin to perceive less risk and demand a lower interest rate.

The simulation model consists of four sectors: Market (prospect pipeline), HR (human resources), Operations (business activities), and Finance. Figure 2 presents a stock and flow diagram of the market sector, which is also available to students in the transparent interface. The market consists of commercial buildings that are suitable for the implementation of energy projects. As represented in Figure 2, the adoption process will be extremely long and costly because prospects need to be moved up through the four stages of the adoption process. Potential customers must progress through four stages to become full EPC Adopters: Interested (potential customers interested in this innovative service), Audits in progress (customers who have contracted an energy audit), Projects in progress (projects being implemented) and EPC Adopters. An important implication of this long contract cycle is that there are very significant operating costs and capital expenditure before potential customers can fully deploy EPC and generate revenue. The stock Partners consist of companies that will help ESCO attract new EPC projects. The flow rates that accumulate stocks are determined by the resources allocated to the relevant EPC activities (informing prospects, selling audits, developing and implementing projects). Partners and the WOM effect also influence the inflows of potential clients.

«Figure 2 is about here»

Figure 2. Stock and flow diagram of the market sector

The participants interacted with a realistic simulator of a business venture (based on a real business case (Capelo et al., 2018, 2021)) over a ten-year simulation period, making decisions every six months until the end of the third year, and annually thereafter (the difference in the frequency results from lessons learned during previous use of this simulator in prior unpublished experiments; these showed that in the early years – three,

four – a shorter time span was advisable in order for participants to better understand and control the effects of their decisions). The participants analyze the status of the business and make decisions related to the development of key resources, with the aim being to develop those critical and interrelated resources at appropriate rates and levels in order to maximize value creation.

These decisions include hiring or firing employees and allocating resources to business activities such as informing potential clients, developing business partners, commissioning energy audits, and developing, implementing and executing EPC projects to properly feed the prospect pipeline and generate revenue for the venture. Students analyze the feedback information to make further decisions about staffing and deployment.

The global challenge of this simulation task is to successfully manage the growth of the venture in order to avoid falling into the *death valley* of negative financial performance and start creating value. In particular, the students need to comprehend the development of clients as they work through various stages of an adoption pipeline, until they become full EPC adopters (and start to generate revenue). They need to: recognize and address both delay and stock accumulation effects related to that process; the word-of-mouth (WOM) mechanism associated to the adoption process; the market advantages of developing and using a network of commercial partners; how workforce planning decisions are critical to providing skilled and experienced teams to drive business growth; how learning affects performance; and how important it is to have a balance between the development of business resources and financial constraints. (Capelo et al., 2021). The business case and the simulator model are described in more detail in Capelo et al. (2018, 2021).

Participants and Procedure

The present study is based on an experiment reported by Capelo et al. (2021), which involved two treatment conditions. In order to test the hypotheses, we conducted a laboratory experiment which included an additional treatment group. The experimental groups and corresponding treatment conditions are described as follows: group A - participants who perform the simulation task through an opaque interface and are not involved in debriefing sessions - low DTR, low STD, and low BVD; group B -

participants who complete the simulation task through a transparent interface and are not involved in debriefing sessions - high DTR, low STD, and low BVD; group C - participants who carry out the simulation task through a transparent interface and are engaged in structural and behavioral debriefings - high DTR, high STD (structural debriefing after the first simulation round), and high BVD (behavioral debriefing after the second simulation round).

This laboratory experiment was carried out at ISCTE, a business school in Lisbon. The experiment involved three classes of students on entrepreneurship courses, 66 students in total, none of whom had any prior knowledge about the system dynamics approach and tools (e.g. CLD, SFD). All the participants were graduate students enrolled in a Master of Science in Management. They had a degree in business administration or economics, and their background included mathematics. One of the authors acted as instructor for these classes. Simulation studies have shown that no superior learning effects result from collaborative play (Stouten et al., 2017). This being so, the present laboratory experiment was completed individually in the classroom with no interaction between the students. A different experimental treatment was randomly appointed to each of the three classes: group A (with 22 students), B (with 22 students), and C (with 22 students). Since treatment A consists of the basic conditions (low DTR, low STD and low BVD), group A plays the role of control group. To maintain a relatively controlled instructional setting, each experimental cohort consisted exclusively of students from a single classroom, ensuring uniformity in educational activities within the same physical space. Any deviation could potentially compromise the integrity of the learning environment and undermine the educational outcomes. There was no interaction between the students in the three groups, because each group comprised students enrolled in a different class. The experiment procedure took place over two sessions and involved the following steps (Figure 3).

Session 1. To benefit from the information contained in the CLD and SFD diagrams representing the structure of the simulation model, students must be able to read and interpret these diagrams. Consequently, the students exposed to the more transparent condition (groups B and C) were given a lecture on these SD tools.

«Figure 3 is about here»

Figure 3. Experiment procedure.

Session 2. The students from all the experimental groups completed the simulation task following the steps established in the experiment procedure presented in Figure 3. All the students received a procedural guide detailing all the steps of the simulation task. The participants started the assignment by reading the introduction with the general description and objectives of the simulation task. As indicated in the guide, the overall learning outcomes consist of students' understanding of model dynamics and their performance, which are assessed and compared to appropriate benchmarks. Then they read the instructions on how to access, start and run the simulator. At this stage, the students carried out some simulation rounds to familiarize themselves with the game interfaces and commands. Finally, they conducted the simulation task according to the steps described in the assignment guide. The task involved three simulation rounds. The participants who were not subjected to debriefing sessions (groups A and B) completed all the simulation rounds consecutively and without interruption. Students exposed to the most transparent condition (groups B and C) were advised to access and use the CLD and SFDs provided by the simulator. Before running the second simulation round, students from group C were submitted to a structural debriefing focused on the model variables and relations. As explained in the assignment guide, students were advised to use this session to clear up any doubts they might have about the meaning of the variables, their relationships, as well as any difficulties they might have in reading and interpreting the CLD and SFD. The instructor started this debriefing session by explaining the information contained in the CLD and SFDs to the students in a detailed and understandable manner, progressively addressing the variables and relations in the simulator model. All doubts concerning the model variables and their relations were clarified. After performing the second simulation round, the students from group C participated in a behavioral debriefing, which focused on helping them to overcome their misunderstandings about the relationship between specific model structures, patterns of action, associated expected behaviors, and consequences in terms of performance. Students were encouraged to use this debriefing session to pay attention to the instructor's presentation, to reflect on their experience of the simulation so far, and to clarify any doubts they may have about how to achieve the desired business behavior

and the pattern of action that leads to such performance. The instructor explained the reference modes (using graphical format) for the critical variables (value creation, clients/prospects, and human resources), their relation to the model structure (presenting relevant parts included in the CLD and SFDs of the simulator model) corresponding desirable and “fear” scenarios, and patterns of actions to be taken into consideration in order to avoid those “fear” scenarios and effectively manage venture resources to support sustainable growth and ultimately succeed in the simulation task. For example, in the case of the client base development, the instructor explained the “fear” and desirable scenarios for prospect acquisition, how it relates to the adoption pipeline structure (including the word-of-mouth mechanism), and what patterns of actions would efficiently drive prospects from potential to full adopters, avoiding imbalances in the adoption stages and waste of resources. All the doubts raised by students were clarified, and thus shared by all students in the treatment group. Each debriefing session was developed for the specific group, with no interaction occurring between students.

Research Variables and Data Treatment

This section describes the use of the variables defined in the research model and corresponding data treatment.

The present study aims to explore the moderation effect that simulation debriefing has on the impact of model transparency on learning and performance in a complex dynamic task. The experiment’s measurements are related to the students’ comprehension of the structure and behavior of the simulated system, and to their performance in the simulation task. Throughout the simulation task, the students repeatedly appreciate, conceptualize, and predict the model dynamics, then they formulate and implement strategies which incorporate their understanding of the structure and behavior of the simulator model. In order to define successful strategies and make effective decisions, students need to develop appropriate understanding (or mental models) of the problem dynamics. The students’ comprehension is then assessed, based on their actions and the corresponding outcomes associated with specific dynamic aspects of the simulation task.

The learning outcomes, model dynamics comprehension and performance are assessed and compared with reference values. This technique has been used in previous experiments (e.g., Diehl & Sterman, 1995; Kopainsky et al., 2015).

Degree of transparency (DTR) – this variable represents the transparency level of the simulator structure. The degree of transparency indicates the extent to which the simulator interface shows the critical variables and relations incorporated in the simulation model. This variable features two levels. In the low level (coded as -1), the participants during the simulation task do not have access to information regarding the structure of the model. In the high level (coded as +1), participants can visualize the CLD and some SFDs of the simulator model.

As already mentioned in the hypotheses section, the term "previous debriefing" in the definition of the following variables means that the debriefing session was applied to some of the previous simulation rounds.

Structural debriefing (STD) – this variable indicates to what extent the instructional method includes a previous debriefing session focused on the variables and relations of the simulation model. This variable features two levels. In the low level (coded as -1), the subjects did not participate in a previous structural debriefing. In the high level (coded as +1), the participants will have been submitted previously to a structural debriefing.

Behavioral debriefing (BVD) – this variable denotes the extent to which the instructional approach incorporates a pre-session debriefing focused on the interplay among model structure, action patterns, system behavior, and performance. This variable features two levels. In the low level (coded as -1), the subjects did not participate in a previous behavioral debriefing. In the high degree (coded as +1) the participants will have been submitted previously to a behavioral debriefing.

Number of the simulation round (NR) - the multivariate analysis considered this independent variable to be the one that controls the effects of the number of simulation iterations. This independent control variable is coded as 1, 2, or 3 (simulation round 1, 2, or 3).

Understanding of model dynamics (DYN) - This metric assesses the degree to which students comprehend the architecture of the simulation model and are able to mentally replicate the dynamic behavior of firm expansion. A good comprehension of the model

dynamics is necessary in order to consistently take effective action. This variable is calculated based on subjects' decision patterns throughout the simulation task and is obtained by analyzing how consistently they can deal with certain dynamic structures of the simulation model. The assumption is that students' actions reflect their comprehension of those critical dynamical structures. The mean value of four constituent elements (generated by the simulation model) is utilized for calculating this parameter, which is evaluated on a continuous spectrum (ranging from 0 to 1) relative to predefined lower and upper limits, following the methodology outlined by Capelo et al. (2021).

Performance (MVA) – The simulation task's efficacy is assessed based on the financial impact generated by the enterprise, as denoted by the ultimate value of the parameter MVA (market value added). This outcome variable is evaluated on a continuous spectrum (ranging from 0 to 1) relative to predefined minimum and maximum benchmarks of MVA. The results are analyzed and the research hypotheses are tested as follows. (i) To evaluate the progression of each treatment group in the simulation task, independent-sample t-tests are utilized to assess differences in means for the variables DYN and MVA between pairs of simulation rounds within treatment groups. Additionally, independent-sample t-tests are employed to compare the outcomes between pairs of treatment groups within simulation rounds, focusing on differences in means for the variables DYN and MVA; ; (ii) In order to compare the degree of outcome improvement (throughout the simulation task) between treatment groups, independent sample t-tests of significance are used to test for the differences in means for the variables IDYN and IMVA between pairs of treatment groups within comparisons of simulation rounds. (iii) Multivariate regression analyses of DYN and MVA on the independent variables are also used to test the hypotheses.

Results and Discussion

The average and standard deviation measurements of the dependent variables DYN and MVA across the three experimental groups are detailed in Table 1. The initial round of the simulation task exhibited the smallest average values for both DYN and MVA, demonstrating uniformity across all experimental groups. The highest mean values for the dependent variables occurred in the third simulation round for the experimental

group C (transparent model simulation with structural and behavioral debriefings). They exhibited, on average, the best DYN (mean = 0.46) and the best MVA (mean = 0.46). In the second round of the simulation, the highest mean values are also associated with the experimental group C (transparent model simulation with structural debriefing) (mean DYN = 0.31, mean MVA = 0.25). As can be seen in Table 1, participants in Group C (transparent model simulation with debriefings) consistently improve their comprehension and performance as they progress through the simulation task from round 1 to round 3, whereas group A (control group/opaque model simulation) and group B (transparent model simulation) only seem to significantly improve their scores from round 1 to round 2.

Table 1. *Means and standard deviations for variables DYN and MVA for each simulation round and experimental group.*

«Table 1 is about here»

Table 2 shows the results of independent sample *t*-test of significance for differences in means for the dependent variables DYN and MVA between pairs of simulation rounds within experimental groups. In order to assess the strength of the difference between the groups, a T-test effect size was applied using Cohen's *d* measure (reference values: $d > 0.2$ - small effect; $d > 0.5$ - moderate effect; and $d > 0.8$ - large effect).

As can be observed in Table 2, the differences in the means of DYN and MVA for the pair "simulation round 2 - simulation round 1" are significant for all three experimental groups (at $p < .1$ for groups A and B, and at $p < .01$ for group C), indicating that, on average, comprehension and performance are improved in all experimental groups from the first to the second round. It must be noted that the differences in the means of group C (transparent model simulator with additional structural debriefing in the second round) are higher in terms of value, significance, and strength than those of the other groups (mean difference DYN = 0.115, $p = .001$, $d = 0.897$; mean difference MVA = 0.158, $p = .001$, $d = 1.140$) which seems to suggest a positive effect of structural debriefing on the dependent variables. With regard to the pair "simulation round 3 - simulation round 2", although groups A and B, on average, improved their DYN and

MVA (group A: mean difference DYN = 0.002, $p = .485$, mean difference MVA = 0.033, $p = .201$; group B: mean difference DYN = 0.010, $p = .417$, mean difference MVA = 0.014, $p = .412$), these differences are small and not significant ($p > .1$). These results indicate that, on average, the groups A (opaque model simulator) and B (transparent model simulator without debriefing) do not significantly improve their DYN and MVA from the second to the third round. In fact, the differences in means of the dependent variables are only significant for group C (transparent model simulator and structural debriefing with additional behavioral debriefing in the third round) (mean difference DYN = 0.146, $p = .001$, $d = 1.050$; mean difference MVA = 0.202, $p < .001$, $d = 1.149$), suggesting a strong positive effect of behavioral debriefing on the variables DYN and MVA.

Table 2. *Independent sample t-test of significance for differences in means for the variables DYN and MVA between pairs of simulation rounds within experimental groups.*

«Table 2 is about here»

Table 3 presents the outcomes of an independent-samples t-test assessing the significance of mean disparities between the variables DYN and MVA across simulation rounds. As depicted in Table 3, the mean values of DYN and MVA across each simulation round for experimental group B do not exhibit significant differentiation compared to those of group A (control group/ opaque model simulation) (round 1: mean difference DYN = 0.014, $p = .350$; mean difference MVA = 0.060, $p = .422$; round 2: mean difference DYN = 0.011, $p = .398$; mean difference MVA = 0.039, $p = .227$; round 3: mean difference DYN = 0.020, $p = .341$; mean difference MVA = 0.019, $p = .354$). These results indicate that a higher degree of transparency does not lead to better outcomes, thus suggesting that increasing model transparency alone, does not help students learn and perform more effectively. In respect to the simulation round 2, the difference in means between groups C (transparent model simulation and structural debriefing) and A (control group/ opaque model simulation) for MVA, is significant (mean difference MVA = 0.102, $p = .010$, $d = 0.733$). These findings

indicate that, on average, participants who combine model transparency with previous structural debriefing perform better than those using the opaque model simulation. In other words, the results suggest a positive joint effect of transparency and previous structural debriefing on performance. Within simulation round 3, there are significant and strong differences in means between groups C (transparent model simulation with structural and behavioral debriefings) and A (control group/ opaque model simulation) (mean difference DYN = 0.174, $p < .001$, $d = 1.181$; mean difference MVA = 0.270, $p < .001$, $d = 1.595$), as well as for between groups C and B (transparent model simulation without debriefings) (mean difference DYN = 0.154, $p = .001$, $d = 0.974$; mean difference MVA = 0.251, $p < .001$, $d = 1.269$), for both dependent variables. The findings indicate that, on average, individuals who integrate model transparency with prior structural and behavioral debriefings exhibit enhanced comprehension and performance compared to those utilizing either opaque model simulation or transparent model simulation separately. These results indicate that, when combined with model transparency, prior structural and behavioral briefings yield cumulative beneficial impacts on task outcomes.

Table 3. Conduct independent sample t-tests to assess significance in mean differences for variables DYN and MVA among pairs of experimental groups across simulation rounds.

«Table 3 is about here»

The participants from group B interacted with a more transparent simulation model as they were able to access and appreciate the structural information provided by causal-loop-diagram and some stock-and-flow diagrams of the simulator model, whereas group A (control group) participants had no access to information about the model structure and behavior. Nevertheless, group B (transparent model simulation) did not exhibit superior task outcomes than group A (opaque model simulation) in terms of understanding the model dynamics and performance. With regard to experimental group C, because its participants had previously been subjected to a structural debriefing (between simulation rounds 1 and 2), they were able to resolve any doubts about the

interpretation of the structural information provided by the diagrams included in the transparent model simulation. This improved their understanding of the structure of the simulator model and they were therefore better able to address critical variables and relationships. However, in comparison with group B participants (transparent model simulation without structural debriefing), group C participants (transparent model simulation with structural debriefing), on average, showed no significantly better understanding and performance (mean difference DYN = 0.019, $p = .336$; mean difference MVA = 0.063, $p = .131$). These findings seem to highlight a common learning difficulty identified in the systems dynamics literature (Davidsen & Spector, 2015): i.e. it is difficult to develop an understanding of how the behavior of a complex system emerges from its underlying causal structure. Between the second and third simulation rounds, the students in Group C participated in a behavioral debriefing. In this debriefing session they were able to expose, discuss, and receive explanations from the instructor which helped them to overcome their misunderstandings regarding the relationship between specific model structures, action patterns and associated expected behaviors. These results strongly suggest that this debriefing process enhanced their knowledge of the structure and dynamics of the simulator and therefore enabled them to achieve better performance outcomes.

Table 4 displays the results of multivariate regression analyses of DYN and MVA on the independent variables DTR, STD, BVD, and NR. Regression analysis for DYN on the independent variables reveals no significant effects for DTR ($\beta = 0.018$, $p = .797$), and STD ($\beta = 0.122$, $p = .178$), and significant effects for BVD ($\beta = 0.211$, $p = .020$), and SR ($\beta = .222$, $p = .003$). Regression analysis of MVA displays no significant effects for DTR ($\beta = 0.042$, $p = .512$), and significant effects for STD ($\beta = .208$, $p = .013$), BVD ($\beta = .257$, $p = .002$), and SR ($\beta = .225$, $p < .001$). These results support three of the six hypotheses. As indicated in Table 3, the mean values of DYN and MVA (within simulation rounds) for experimental group B (high DTR, low STD, and low BVD) were not significantly different from those for experimental group A/the control group (low DTR, low STD, and low BVD). Furthermore, between simulation rounds 2 and 3, the participants in group B, like those in the group A, did not significantly improve their comprehension and performance (Table 2). Also, the regression (Table 4) did not show significant effects (at .05 significance level) of DTR on DYN and MVA. Consequently,

our research does not provide support for hypotheses H1 (the degree of transparency of the simulation model positively influences understanding of the model dynamics) and H2 (the degree of transparency of the simulation model positively influences performance).

Table 4. *Regression outcomes for each of the independent variables.*

«Table 4 is about here»

As discussed previously, the results presented in Table 2 and table 3 suggest that STD positively moderates the impact of DTR on MVA. Additionally, as the structural debriefing session complements the transparent model simulation (high DTR), a significant effect of STD on MVA (Table 4) also supports the existence of that moderation effect. Therefore, these results substantiate hypothesis H4 (prior structural debriefing combined with model transparency enhances performance / structural debriefing effectively moderates the influence of transparency level on performance). Nevertheless, our study fails to substantiate hypothesis H3 (prior structural debriefing alongside model transparency enhances comprehension of model dynamics/ structural debriefing moderates positively the effect of transparency level on model dynamics understanding). . As indicated in Table 3, in simulation round 2, the participants from group C (transparent model simulation with structural debriefing) did not exhibit better model comprehension than those from groups A (opaque model simulation) and B (transparent model simulation without debriefing). Also, the regression results (Table 4) do not present a significant effect (at .05 significance level) of STD on DYN. As indicated by Table 2 and Table 3, the variable BVD seems to positively moderate the joint effect of DTR and STD on DYN and MVA. The previous behavioral debriefing complements the previous structural debriefing in the transparent model simulation approach. Consequently, the regression results (Table 4) indicate to what extent BVD moderates the joint effect of STD and DTR on DYN and MVA. Therefore, regression results also support hypothesis H5 (previous behavioral debriefing - combined with model transparency and previous structural debriefing - positively influences understanding of model dynamics / behavioral debriefing positively

moderates the joint effect that The impact of transparency degree and structural debriefing on the comprehension level of model dynamics, and hypothesis H6 (prior behavioral debriefing - in conjunction with model transparency and prior structural debriefing - enhances performance / behavioral debriefing moderates positively the combined impact of transparency degree and structural debriefing on performance. As predicted, the outcomes provide strong evidence that the behavioral debriefing provided participants with a potent tool for contemplating the connection between model structure and behavior, thereby expediting their comprehension of the dynamics of the simulated system and improving their performance.

Limitations and future research

The similarity between the structure and behavior of the students' mental models and the structure and behavior of the simulation model was not measured directly in the experiment and could, therefore, be a matter for future research. Instead, the present study used the variable DYN to assess the student's comprehension of model dynamics. The present study analyzed the combined effects of progressively adding model transparency, previous structural debriefing, and previous behavioral debriefing. Further research might consider a research design that would permit investigation of the individual impacts of these experiment conditions. Another study might investigate the effects of combining structural and behavioral debriefings in the same session. Additionally, several potential methodological limitations to the current investigation exist. The research method was based on a quasi-experimental design, as there was no random allocation of students to the experimental and control groups. Standardized student-teacher relationships and classroom features were also difficult to control.

Conclusion

In order to contribute to the ongoing research described in the question posed - what type of instructional support needs to be offered to enable learners to take full advantage of transparent model simulations? – A pedagogical study was implemented to evaluate a collection of hypotheses designed to examine the moderating influence of prior structural and behavioral debriefing on the effect of model transparency on learning and performance in a sophisticated dynamic task. The findings from the t-test and regression

analysis validate three out of six hypotheses. Hypotheses H1 (the level of transparency positively impacts the comprehension of model dynamics) and H2 (the level of transparency positively impacts performance) are not validated. Contrary to the hypotheses formulated, the results of this study reveal that, in terms of learning and performance, a simulation approach is not made more effective by additionally showing students the diagrams of the simulator model. Consequently, a practical implication of the above revelations is that an SBLE model does not become more transparent and understandable to students simply by making the diagrams of the simulator model visible. These results are convergent with previous studies (e.g. Capelo & Dias, 2009a; Capelo & Silva, 2020; 2005; Kopainsky & Alessi, 2015) that also revealed the limited effects of using more transparent conditions. In order to benefit from the information contained in the CLD and SFD diagrams representing the structure of the simulation model, students must be able to read and interpret these diagrams. Otherwise, students will not benefit from accessing this additional information, which will only distract them from their learning (Groesser, 2012). In line with the previous condition, the results can be explained by the fact that the students, despite having previously received a lecture on CLDs and SFDs, were not sufficiently familiar with the tools of system dynamics and were therefore not fully able to read and interpret the diagrams of the model correctly.

The results of this experiment lead us to conclude that students who interacted with a more transparent model simulator and were previously involved in structural debriefing significantly improved their performance, which supports hypothesis H4 . This conclusion is in line with previous research on the learning effects of model transparency. Machuca (2000) found that transparent model simulations facilitate management learning about organizational complexity, and the simulation experiment conducted by Größler et al. (2000) also showed positive performance effects of model transparency. Similarly, Qudrat-Ullah (2007) also discovered that engaging students in pre-discussions about the model structure enhanced their mental models and task performance. Additionally, these results seem to reinforce the idea that emerged from previous studies (e.g. Capelo & Dias, 2009a; Capelo & Silva, 2020; Kopainsky et al., 2015; Elsayah et al., 2017; Van Borkulo et al., 2012) which is that participants need to be subjected to specific complementary instructional strategies to facilitate

comprehension of the model structure. However, the findings of the current study do not corroborate hypothesis H3 (prior structured debriefing combined with model transparency positively impacts comprehension of model dynamics/structured debriefing positively moderates the effect that transparency degree has on understanding model dynamics). From the result of the test of hypothesis H4 we can conclude that the students improved their control of the simulation task thanks to the additional information provided by the transparent interface. However, the sequences of simulation decisions made by participants who received the model transparency and structural debriefing treatment did not evidence that they consistently enhanced their understanding of the simulator dynamics. These results are in line with the results of the experiment conducted by Capelo & Silva (2020), which concluded that although a simulator transparency strategy helps students to identify certain causal structures in the model, they are not able to correctly infer the dynamic behavior of the simulator model. This deduction is consistent with a cognitive limitation frequently mentioned in the literature (e.g. Davidsen & Spector, 2015; Schaffernicht, 2010): i.e. individuals have difficulty in comprehending how the behavior of a complex system stems from its causal structure. In light of the mental model (of a dynamic system) theory, which asserts that mental models are cognitive mechanisms that comprise knowledge about the structure and behavior of the external system (Doyle & Ford, 1998), these findings seem to configure the type of mental model deficiency related to failure in acknowledging relevant dynamic behaviors that emerge from the system structure (Sterman, 1994). The findings validate hypothesis H5 (earlier behavioral review - integrated with model transparency and earlier structural review - positively affects the comprehension of model dynamics / behavioral review positively moderates the combined impact of transparency and structural review on understanding model dynamics) and hypothesis H6 (earlier behavioral review - integrated with model transparency and earlier structural review - positively affects performance / behavioral review positively moderates the combined impact of transparency and structural review on performance). As predicted, the results of the present study provide strong evidence that the combination of previous structural and behavioral debriefing provided subjects with an effective learning approach that helped them to correctly identify and understand the critical causal structures of the simulator model and to infer the dynamic behavior that resulted from

these structures. This significantly improved their ability to deal with the dynamics of the simulated system and improved performance. One possible explanation is that, in the first simulation round, students tend to rush into trying the first strategy that comes to mind rather than thinking carefully to identify the critical causal structures and behaviors. In the second round (after the structural debriefing), their mental models may still lack completeness and coherence, may be ambiguous and, most importantly, may fail to acknowledge dynamic behavior. After undergoing behavioral debriefing, students were more aware of critical behaviors that emerge from the few causal structures that most determine task performance. Consequently, they were able to dedicate and direct their (limited) cognitive resources towards the most relevant information.

These results are consistent with previous research, namely the findings reported by Sengupta and Abdel-Hamid (1993) that cognitive feedback and feedforward favor performance, by Richardson et al. (1994) that to affect performance, conditions need to both influence the design logic level and the operator logic level, and by Qudrat-Ullah (2020) that process-oriented debriefing is adequate for acquiring decision-making skills in dynamic tasks. Overall, the findings of our investigation corroborate a premise previously identified in earlier studies (e.g. Diehl & Sterman, 1995; Sterman, 1989) that learners encounter two types of challenges - i) misunderstandings of the system architecture and ii) misunderstandings of the dynamic behaviors arising from the system architecture – hence it is crucial to offer facilitation to enhance a subject's performance and comprehension of system dynamics (e.g. Capelo & Dias, 2009b; Kopainsky & Sawicka, 2011; Qudrat-Ullah, 2014, 2020).

Regarding the ramifications for the evolution of SBLEs, the findings of this research offer robust proof that an SBLE aimed at education in intricate and fluid fields can gain advantages from a pedagogical approach that merges model transparency (via an interface displaying key aspects of the model's architecture and actions) with a methodical application of structural and behavioral debriefing during the simulation phases. In the present experiment, the more transparent interface includes a control panel that shows the student both a critical stock-and-flow structure of the model and its corresponding behavior. As observed in the transparent condition without previous debriefing, although students had access to this critical structural information, they had difficulty recognizing the relevant dynamic behaviors that emerged from the model

structure. Assuming that a mental model (of a dynamic system) can include structural and behavioral elements of the external system being represented, and that previous research has shown that mental models are subject to misperceptions of system structure (variables and causal relations) and misperceptions of the dynamic behavior that emerges from dynamically complex structures, these findings seem to suggest that in such an experimental condition, students' mental models may not be able to adequately represent the external system (simulator model). On the other hand, according to the hypotheses formulated, the results seem to indicate that the debriefing sessions effectively supported and directed the students' (limited) cognitive resources to certain critical structural and behavioral aspects of the simulator model that are fundamental for success in the simulation task. In other words, this approach seems to provide students with the opportunity to develop more accurate knowledge (mental models) of the model structure and behavior, to more accurately anticipate the consequences of possible courses of action, and to improve task performance.

This experiment also contributes to ongoing research on learning and decision making in complex and dynamic environments. The results appear to indicate that for decision-makers to achieve success, it is not enough for them to simply obtain precise data regarding contextual variables and interconnections. In order to mentally infer the likely outcomes of policy actions, decision-makers' mental models must also be informed about dynamic behaviors that emerge from critical causal structures. These findings reinforce the need to investigate and discover approaches to effectively inform and improve decision-makers' mental models.

The results of this research also enhance the field of system dynamics by reaffirming the importance of utilizing educational simulators, alongside specific pedagogical techniques, as a core strategy for optimizing performance and comprehension in intricate and dynamic activities.

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Table 1. Means and standard deviations for variables DYN and MVA for each simulation round and experimental group.

		DYN - Understanding of the model dynamics			MVA - Performance	
Treatment	Description	N	Mean	SD	Mean	SD
Round 1						
A	Low DTR, low STD, low BVD	22	0.22	0.12	0.10	0.11
B	High DTR, low STD, low BVD	22	0.23	0.12	0.10	0.10
C	High DTR, low STD, low BVD	22	0.20	0.12	0.10	0.12
Round 2						
A	Low DTR, low STD, low BVD	22	0.28	0.13	0.15	0.12
B	High DTR, low STD, low BVD	22	0.29	0.15	0.19	0.21
C	High DTR, high STD, low BVD	22	0.31	0.13	0.25	0.15
Round 3						
A	Low DTR, low STD, low BVD	22	0.28	0.15	0.19	0.14
B	High DTR, low STD, low BVD	22	0.30	0.17	0.21	0.20
C	High DTR, high STD, high BVD	22	0.46	0.14	0.46	0.20

Variable definition:

DTR - Degree of Transparency; Low DTR: Subjects do not have access to information about the structure of the model; High DTR: Subjects can visualize the CLD and some SFDs of the simulator model.

STD - Structural Debriefing; Low STD: Subjects did not participate in a prior structural debriefing; High STD: Subjects will have been submitted previously to a structural debriefing.

BVD - Behavioral Debriefing; Low BVD: Subjects did not participate in a prior behavioral debriefing; High BVD: Subjects will have been submitted previously to a behavioral debriefing.

Table 2. *Independent sample t-test of significance for differences in means for the variables DYN and MVA between pairs of simulation rounds within experimental groups.*

Treatment	DYN - Understanding of the model dynamics			MVA - Performance		
	Mean Differ.	Cohen's d ^a	p-value	Mean Differ.	Cohen's d ^a	p-value
<i>Round 2 - Round 1</i>						
A - Low DTR, low STD, low BVD	0.066*	0.515	.048	0.054*	0.470	.063
B - High DTR, low STD, low BVD	0.062*	0.448	.073	0.087*	0.531	.044
C - High DTR, high STD - low STD, low BVD	0.115**	0.897	.001	0.158**	1.140	.001
<i>Round 3 - Round 2</i>						
A - Low DTR, low STD, low BVD	0.002	0.011	.485	0.033	0.255	.201
B - High DTR, low STD, low BVD	0.010	0.063	.417	0.014	0.067	.412
C - High DTR, high STD, high BVD - low BVD	0.146**	1.050	.001	0.202**	1.149	.000

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

a. *t*-test effect size using Cohen's d measure. Reference values: $d > 0.2$ (small effect), $d > 0.5$ (moderate effect), and $d > 0.8$ (large effect).

Variable definition:

DTR - Degree of Transparency; Low DTR: Subjects do not have access to information about the structure of the model; High DTR: Subjects can visualize the CLD and some SFDs of the simulator model.

STD - Structural Debriefing; Low STD: Subjects did not participate in a prior structural debriefing; High STD: Subjects will have been submitted previously to a structural debriefing.

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Table 3. *Independent sample t-tests of significance for differences in means for the variables DYN and MVA between pairs of experimental groups within simulation rounds.*

Pair	DYN - Understanding of the model dynamics			MVA - Performance		
	Mean Differ.	Cohen's d ^a	p-value	Mean Differ.	Cohen's d ^a	p-value
<i>Round 1</i>						
B (high DTR) - A (low DTR)	0.014	0.117	.350	0.006	0.060	.422
C (high DTR) - A (low DTR)	-0.020	-0.162	.297	-0.002	-0.017	.478
C (high DTR) - B (high DTR)	-0.034	-0.278	.181	-0.008	-0.072	.407
<i>Round 2</i>						
B (high DTR/low STD) - A (low DTR/STD)	0.011	0.079	.398	0.039	0.228	.227
C (high DTR/STD) - A (low DTR /STD)	0.030	0.224	.231	0.102*	0.733	.010
C (high DTR/STD) - B (high DTR/low STD)	0.019	0.128	.336	0.063	0.343	.131
<i>Round 3</i>						
B (high DTR/low STD/BVD) - A (low DTR/STD/ BVD)	0.020	0.124	.341	0.019	0.114	.354
C (high DTR/STD/BVD) - A (low DTR/ STD/ BVD)	0.174**	1.181	.000	0.270**	1.595	.000
C (high DTR/STD/BVD) - B (high DTR/low STD/ BVD)	0.154**	0.974	.001	0.251**	1.269	.000

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

a. T-test effect size using Cohen's d measure. Reference values: $d > 0.2$ (small effect), $d > 0.5$ (moderate effect), and $d > 0.8$ (large effect).

Variable definition:

DTR - Degree of Transparency; Low DTR: Subjects do not have access to information about the structure of the model; High DTR: Subjects can visualize the CLD and some SFDs of the simulator model.

STD - Structural Debriefing; Low STD: Subjects did not participate in a prior structural debriefing; High STD: Subjects will have been submitted previously to a structural debriefing.

BVD - Behavioral Debriefing; Low BVD: Subjects did not participate in a prior behavioral debriefing; High BVD: Subjects will have been submitted previously to a behavioral debriefing.

Table 4. *Regression results for all independent variables.*

Independent Variables	Dependent Variables			
	DYN - Understanding of the model dynamics		MVA - Performance	
	Standardized Beta	<i>p</i> -value	Standardized Beta	<i>p</i> -value
DTR - Degree of Transparency	.018	.797	.042	.512
STD - Structural Debriefing	.122	.178	.208*	.013
BVD - Behavioral Debriefing	.211*	.020	.257**	.002
NR – Number of Simulation Round	.222**	.002	.225**	.000
Adjusted R ² (Significance)	.188 (.001)		.311 (.001)	

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