Task Complexity and Cognitive Load in Simulation-based Education

Received: 12 April 2022 | Revised: 12 September 2022 | Accepted: 21 September 2022
DOI: 10.1111/medu.14941

RESEARCH ARTICLE

Task complexity and cognitive load in simulation-based education: A randomised trial

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Funding information
None.

Abstract

Introduction: When designing simulation for novices, educators aim to design tasks and environments that are complex enough to promote learning but not too complex to compromise task performance and cause cognitive overload. This study aimed to determine the impact of modulating task and environment complexity on novices' performance and cognitive load during simulation.

Methods: Second-year pharmacy students (N = 162) were randomly assigned to one of four conditions (2 × 2 factorial design) in simulation: simple task in simple environment, complex task in simple environment, simple task in complex environment and complex task in complex environment. Using video recordings, two raters assessed students' performance during the simulation. We measured intrinsic cognitive load (ICL) and extraneous cognitive load (ECL) with questionnaires after the task and tested knowledge after task and debriefing.

Results: Mean performance scores in simple environment were 28.2/32 (SD = 3.8) for simple task and 25.8/32 (SD = 4.2) for complex task. In complex environment, mean performance scores were 24.6/32 (SD = 5.2) for simple task and 25.6/32 (SD = 5.3) for complex task. We found significant interaction effects between task and environment complexity for performance. In simple environment, mean ICL scores were 4.2/10 (SD = 2.2) for simple task and 5.7/10 (SD = 1.5) for complex task. In complex environment, mean ICL scores were 4.9/10 (SD = 1.8) for simple task and 5.1/10 (SD = 1.9) for complex task. There was a main effect of task complexity on ICL. For ECL, we found neither an interaction effect nor main effects of task and environment complexity. There was a main effect of task complexity on knowledge test after task and main effects of both task and environment complexity on knowledge after debriefing.

Conclusions: Performance was good, and cognitive load remained reasonable in all conditions, which suggests that, despite increased complexity, students seemed to strategically manage their own cognitive load and learn from the simulations. Our findings also indicate that environmental complexity contributes to ICL.

This manuscript, including tables, figures and appendices, is the original work of the authors.

1 | INTRODUCTION

For novices, experiencing authentic clinical tasks in a controlled environment with simulated patients allows them to safely integrate knowledge, skills and attitudes required in the workplace. The learning tasks in simulation can be challenging for novices, since they have limited clinical experience and are still consolidating newly acquired cognitive schemas.[1] The dynamic learning environment is also highly engaging both cognitively and emotionally and can directly influence what students learn.[2,3] When mixing such complex learning tasks with a complex learning environment, inexperienced learners may potentially experience cognitive overload and be at risk of negative impact on learning. Although modulating task and environment complexity is part of every simulation design, the combined effect of these two components on novices' learning process remains unclear.

1.1 | Cognitive load theory

Cognitive load experienced during a simulation highly depends on the interactions between the learner, the simulation task and the learning environment.[4,5] The greater the interactions, the higher the cognitive load for that learner. Cognitive load theory distinguishes two types of cognitive load, namely, intrinsic cognitive load and extraneous cognitive load. The intrinsic load relates to the complexity of information and the degree of interacting elements. Extraneous cognitive load refers to any additional load that does not pertain to the learning goals. The original cognitive load theory model describes a third type of load, namely, germane load, which refers to the working memory resources involved in processing intrinsic cognitive load.[5] In a clinical environment, whether simulated or real, germane cognitive load seems to play a limited role and will therefore not be the focus of this research.[6] In simulation, both the task and the environment contribute to intrinsic load because these two features comprise relevant information that needs to be processed by the learner to perform the task.[6] To optimise learning, extraneous cognitive load must be minimised to allow learners to focus their working memory resources on dealing with an essential element.[7]

A reconceptualisation of the cognitive load theory proposed by Choi et al.[4] considers the learning environment as a determinant of the effectiveness of instruction. In their revised model of this theory, the learning task and the environment are disentangled. The *environment* refers to the whole range of physical features of a place in which teaching and learning occur. These features include physical characteristics of learning materials and tools (i.e. the media through which the information is presented to the learner), physical properties of the room and the physical presence of other people. In other words, it comprises all the sensory stimuli generated by the environment that can be perceived by the human senses. The *learning task* characteristics, for example, the patient's medication profile or the information to be communicated to the patient, refer to the intrinsic task complexity or the type of tasks to be executed. The authors explain that what will constitute intrinsic or extraneous cognitive load will depend on the learner's expertise level and will result from the design of both the task and the environment.

1.2 | Adapting tasks and environments for novices

In simulation-based education, complexity should be adapted to the learners' expertise level and increased progressively as they become more proficient.[8] Task complexity is mainly determined by the *number* of information elements to process and the *degree of interaction* between them.[7] From the novices' perspective, complex tasks are highly valuable as they provide opportunities during debriefings to learn from ones' mistakes.[1] In simulation, the learning tasks are situated in a simulated clinical environment, which adds context to this task and allows students to incorporate environmental features in their decision-making process.[6,9,10] This learning environment can seem complex for an inexperienced learner.[2] Unlike a real clinical environment, a simulated environment can be controlled by decreasing the *element interactivity* in the learner's working memory without compromising its authenticity. When designing simulation for novices, it is advisable to first remove elements that can typically be found in a real 'messy' clinical environment that do not pertain to the learning goal and may contribute to extraneous cognitive load (e.g. ambient noise in the pharmacy). Environmental complexity can also be modulated by presenting the information to the learner in either a simple or a complex way. For example, a disorganised electronic patient record (EPR) reflects a complex environmental feature with high element interactivity as opposed to a well-organised EPR that comprises the *same information* than a complex one but that facilitates the retrieval of relevant information to accomplish the learning task. Therefore, learners do not need to invest too much mental effort in processing the functioning of the EPR and can devote their cognitive resources in solving the clinical problem.

1.3 | The combined effect of complex tasks and environments

Although both the learning task and the environment can be adapted to take into account the learner's ability, increasing evidence indicates that modulations made in the learning environment to accommodate learners' skill level might influence their capacity to attend to specific learning goals.[11–13] In simulated environments, multiple studies have shown enhanced learning among novices for simple skills training[14,15] but equivocal results in terms of complex skills acquisition such as clinical reasoning.[16–18] LaRochelle et al.[17] found that clinical reasoning skills of undergraduate medical students improved as authenticity increased for top students and for the bottom tertile of the cohort. Contrastingly, performance decreased as authenticity increased for students in the middle tertile, thus failing to demonstrate the consistent superiority of increased authenticity on novices' performance. The authors postulate that increased authenticity might provoke extraneous cognitive load, which can explain why some students do not benefit from this instructional change. However, they could not entirely explain why only middle students would be subjected to this increase in extraneous cognitive load. Learning complex skills in a complex environment is likely to be overwhelming for a novice learner, partly because of their lack of experience with both the task and the environment. Haji et al.[19] have demonstrated that novices perform better and experience lower cognitive load when learning a simple task in a complex environment than when learning a complex task in a complex environment. It is still unclear whether modulating environment complexity would lead to better skills acquisition for complex tasks. Since simulation requires considerable resources, it is imperative that scenarios be optimally designed so that learners can reach learning goals efficiently.

1.4 | Objective of the current study

This study aimed to determine the impact of modulating task and environmental complexity on novices' performance, cognitive load and knowledge in simulation.

2 | METHODS

2.1 | Setting

We conducted this study at Laval University Faculty of Pharmacy (Canada) in the Pharmacy Simulation Laboratory, which replicates 10 pharmacy offices fully equipped with authentic material commonly found in community pharmacies (e.g. medications, EPR, e-resources and books). Every workstation was equipped with a ceiling camera.

2.2 | Participants

All second-year undergraduate pharmacy students (167), in a 4-year competency-based pharmacy programme (PharmD) that is taught in French, were eligible to participate on a voluntary basis. Given their limited clinical experience (i.e. 3 to 4 weeks of clinical internship) prior to the experiment, the participants were considered novices. They had experienced four simulation trainings in the Pharmacy Simulation Laboratory similar to the ones in this experiment prior to recruitment on other subjects.

In the programme, the large cohort of students is originally divided into six groups of approximately 30 students for various educational activities. For this study, stratified random assignment (i.e. random assignment within the predetermined groups of 30) was used to subdivide students into teams of three using a random number generator. An unblinded technician from the Simulation Centre assigned each team to a workstation for a full session. Each session comprised three different learning tasks that require the participation of one student playing the pharmacist's role. Each student played the pharmacist once and observed their peers twice during one simulation session. The order in which they played the pharmacist or the observer was assigned by the unblinded technician using the random numbers generated previously (i.e. of the three students assigned to a station, participants performed the pharmacist in ascending order). The research team involved in analysing the data remained blinded throughout the process.

2.3 | Design

2.3.1 | Experimental conditions

While acting as the pharmacist, students randomly experienced one of the four experimental conditions in a 2×2 factorial design: simple task in simple environment, complex task in simple environment, simple task in complex environment and complex task in complex environment. Each simulation session displayed one experimental condition at a time to facilitate the debriefing. Two simulation experts and pharmacy clinicians designed the tasks and environments. All conditions were pilot-tested prior to the study with a small group of third-year students. Clinical aspects of each case were previously taught in the programme but never in simulation.

Based on the literature, we created a blueprint, presented in Figure 1, to modulate task and environment complexity. Simple and complex learning tasks differed by the increasing number of information elements and the degree of interaction between them. For example, simple tasks involved patients with limited or no comorbidities, taking few or no prescription drugs, as opposed to complex tasks that comprised patients with more comorbidities and taking medication on a regular basis with therefore potential drug interactions. Both simple and complex learning environments were highly authentic and included medication, EPR, telephones and other equipment commonly found in real-life practice. Simple and complex environments differed in terms of element interactivity. For instance, simple environments involved stations that were in order and not visually loaded with drug displays, and clearly written prescriptions. Complex environments displayed visually loaded stations with relevant material, messy handwritten prescriptions and/or visually unclear. In total, 12 different learning tasks were developed (i.e. three different clinical topics, varying in task/environment complexity for the four conditions).

A general briefing at the beginning of the simulation session presented the environmental features and logistical details to consider. During the simulation, 17 different experienced actors played the simulated patients. All students, whether having acted as pharmacists or observers, participated in the debriefing. After this debriefing, a new learner experimented a new learning task followed by its debriefing.

2.4 | Instruments

2.4.1 | Task performance

We used video recordings to assess the performance of each student playing the pharmacist. We developed a global rating scale to

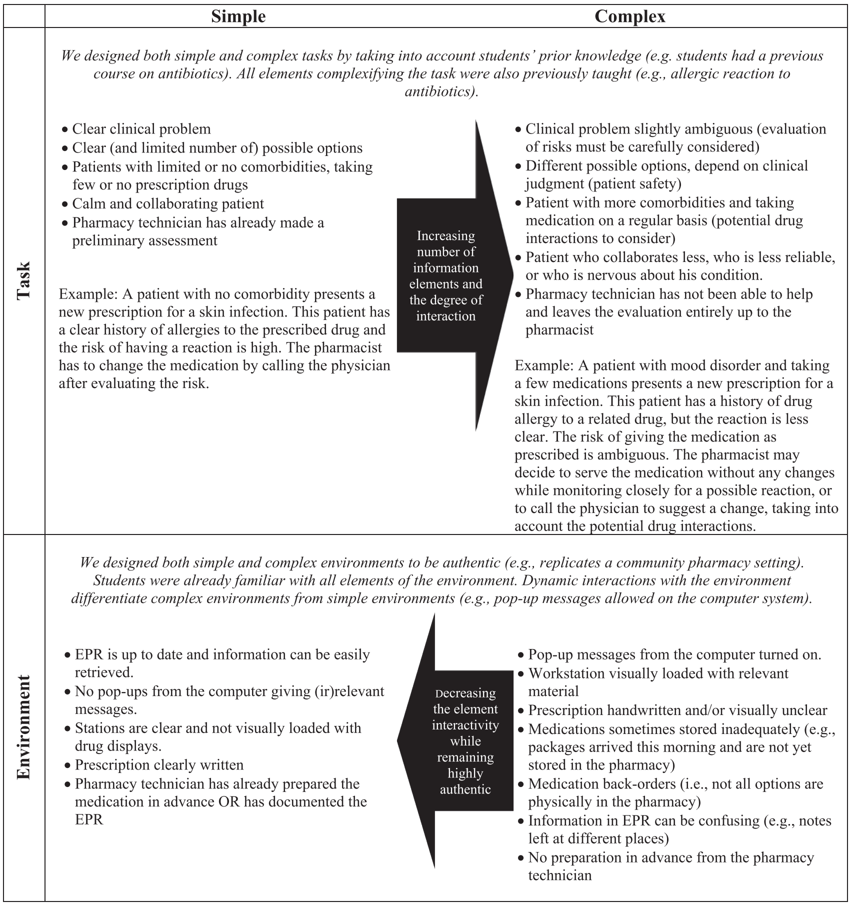

FIGURE 1 Blueprint to modulate task and environment complexity in the design of simulation for novices

assess the quality of the performance (see Appendix S1) based on the Anaesthetist's Non-technical Skills Global Rating Scales (ANTS) rubric, originally designed and validated to assess teams during anaesthesiology trainings.[20] The ANTS system was developed using psychological research techniques to identify and structure non-technical skills. The evaluation process, which involved 50 trained anaesthetists using the instrument while watching eight videos of simulated anaesthetic scenarios, resulted in a satisfactory level of validity, reliability and usability. The original items of the rubric were modified to account for the study context. Eight items were selected because they assessed task or environment management. The eight items were rated from 1 to 4 with a global score minimum 8 to maximum 32 (1 = *Poor*, i.e. performance endangered or potentially endangered patient safety; 2 = *Marginal*, i.e. performance indicated cause of concern, and considerable improvement is needed; 3 = *Acceptable*, i.e. performance was of a satisfactory standard, but it could be improved; and 4 = *Good*, i.e. performance was of a consistently high standard, and it could be used as a positive example for others). The rubric had been piloted prior to the study with the same population during a previous simulation session. The Cronbach's alpha for this adapted tool was 0.80, which provides validity evidence for internal structure. Videos were assigned randomly to two blinded independent raters (MLT and GL), both pharmacists and educators. MLT rated all participants. GL rated 20% of the participants. Interrater reliability on performance scores was 0.64 (substantial), 95% CI [0.55–0.72].

2.4.2 | Cognitive load

We measured intrinsic and extraneous cognitive load after the simulations using a translated (French) and adapted version of a cognitive load questionnaire (see Appendix S2) developed by Leppink et al.[21] The original questionnaire was developed in the context of lectures in statistics and was tested to provide evidence for the validity and reliability of a three-factor solution (i.e. three types of cognitive load).[22] The translation of each item had first been done from English to French by one researcher. Another member of the team then translated back the items from French to English to ensure their appropriateness. Our questionnaire consisted of five items targeting intrinsic cognitive load and five items relating to extraneous cognitive load. Participants rated each item on a scale of 0 to 10 (0 = *not at all*, 10 = *completely the case*). The tool used in this study had previously been used in the context of simulation for undergraduate pharmacy students.[1,2] This version was pilot-tested prior to the intervention with the same students during a simulation session to familiarise participants with the terms and to clarify any imprecision. The Cronbach's alpha for intrinsic cognitive load in this study was 0.9 and 0.77 for extraneous cognitive load.

2.4.3 | Knowledge tests

We measured knowledge through 10 true or false items related to the task participants had just performed. The test was administered after the

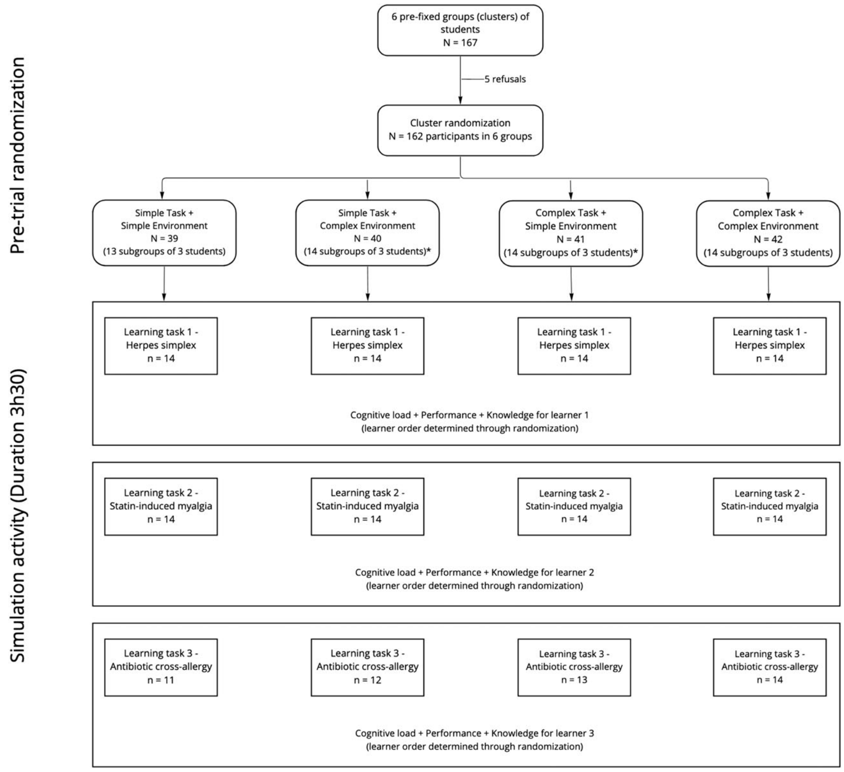

FIGURE 2 Flow diagram of study randomisation process and intervention

simulation and once again after debriefing. The tests were designed by the same team who developed the learning tasks to ensure that the content of the test reflected the intended learning goals. The tests were pilot-tested with third-year students at the same time as the four conditions.

2.5 | Data analysis

We conducted statistical analyses with SPSS Statistics 28 (IBM Corp, Armonk, NY). We performed two-way ANOVAs to determine the main effects and interactions of task complexity and environment complexity on task performance, cognitive load and knowledge test scores. For significant interactions, we conducted follow-up analysis with simple effects to help interpret the results. Due to the number of planned comparisons, Bonferroni corrections were applied, resulting in a *p*-value of significance of 0.01. A post hoc power analysis revealed a power of 0.52.

2.6 | Ethics

This study was approved by the Research Ethics Committee of Laval University (2019-230/03-09-2019).

3 | RESULTS

A total of 162 students agreed to participate in this study (response rate of 97%). They were mostly female (72%) with a mean of 22.0 years old (SD = 2.5) with a college degree (78%) prior to entering the PharmD programme. Just over 27% (n = 43) participants had experienced a case similar to the one they had experienced during the simulation in real-life practice (Figure 2).

As shown in Figure 3, students' mean performance scores in simple environment were 28.2/32 (SD = 3.8) for simple task and 25.8/32 (SD = 4.2) for complex task. In complex environment, mean performance scores were 24.6/32 (SD = 5.2) for simple task and 25.6/32 (SD = 5.3) for complex task. We found a significant interaction effect between task and environment complexity in terms of performance, $F(1–158) = 5.61$, $p = 0.01$, which indicates that the effect of task complexity on performance depends on the level of environment complexity. As this interaction effect was statistically significant, main effects cannot be sensibly interpreted. Simple effect analysis revealed that performance of simple tasks significantly decreased between simple and complex environments ($p < 0.001$). For complex task, performance remained unchanged ($p = 0.89$) between simple and complex environments. There was no significant difference in performance between simple and complex tasks in both simple ($p = 0.02$) and complex environment ($p = 0.33$).

In simple environment, mean intrinsic load scores were 4.2/10 (SD = 2.2) for simple task and 5.7/10 (SD = 1.5) for complex task (see Figure 4). In complex environment students reported a mean intrinsic cognitive load of 4.9/10 (SD = 1.8) for simple task and 5.1/10 (SD = 1.9) for complex task. There was no significant interaction effect between task and environment complexity in terms of intrinsic cognitive load, $F(1–152) = 4.43$, $p = 0.04$. There was a main effect of task complexity ($p = 0.004$) but no main effect of environment complexity ($p = 0.77$) on intrinsic cognitive load. We found no significant

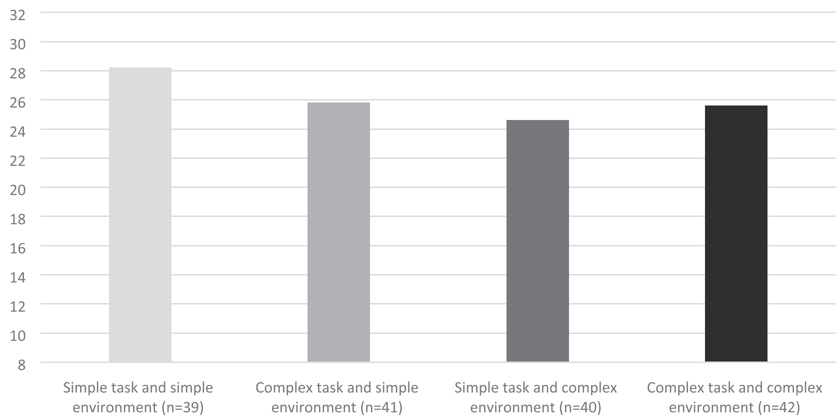

FIGURE 3 Impact of modulating task and environment complexity on students' task performance (scored from 8 to 32). Mean performance scores in simple environment: 28.2/32 (SD = 3.8) for simple task versus 25.8/32 (SD = 4.2) for complex task. In complex environment, mean performance scores: 24.6/32 (SD = 5.2) for simple task versus 25.6/32 (SD = 5.3) for complex task. Significant interaction effect between task complexity and environment complexity (p = 0.01). Simple effect analysis revealed that performance of simple tasks significantly differed between simple and complex environments (p < 0.001). For complex task, performance remained unchanged (p = 0.89) between simple and complex environments. There was no significant difference in performance between simple and complex tasks in both simple (p = 0.02) and complex environment (p = 0.33).

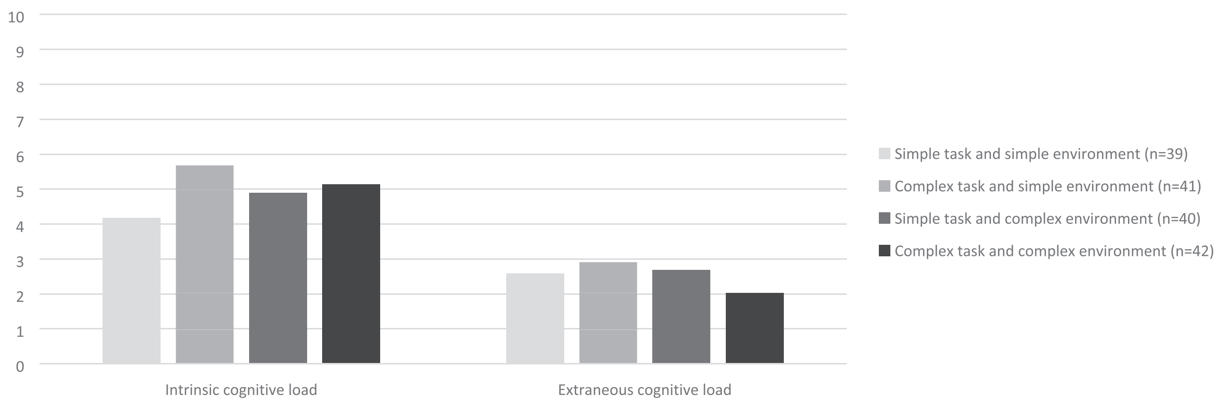

FIGURE 4 Impact of modulating task and environment complexity on students' mean scores of intrinsic cognitive load and extraneous cognitive load (agreement scale from 0 to 10). In simple environment, mean intrinsic load scores were 4.2/10 (SD = 2.2) for simple task and 5.7/10 (SD = 1.5) for complex task. In complex environment, students reported a mean intrinsic cognitive load of 4.9/10 (SD = 1.8) for simple task and 5.1/10 (SD = 1.9) for complex task. No significant interaction effect between task and environment complexity in terms of intrinsic cognitive load, p = 0.04. There was a main effect of task complexity (p = 0.004) but no main effect of environment complexity (p = 0.77) on intrinsic cognitive load. In simple environment, mean extraneous load scores were 2.6/10 (SD = 1.8) for simple task and 2.9/10 (SD = 2.1) for complex task. In complex environment, mean extraneous load scores were 2.7/10 (SD = 1.9) for simple task and 2.1/10 (SD = 1.5) for complex task. No significant interaction effect between task complexity and environment complexity (p = 0.09). No main effect of either task complexity (p = 0.56) or environment complexity (p = 0.19).

interaction effect between task and environment complexity for extraneous cognitive load, $F(1–150) = 2.84$, $p = 0.09$. There was no main effect of either task complexity ($p = 0.56$) or environment complexity ($p = 0.19$) on extraneous cognitive load.

We found no significant interaction effect between task and environment complexity on mean results of knowledge tests, both after task, $F(1–152) = 0.90$, $p = 0.34$, and after debriefing, $F(1–153) = 1.29$, $p = 0.26$ (see Figure 5). There was a main effect of task complexity ($p = 0.01$) and a non-significant main effect of environment complexity ($p = 0.79$) on knowledge test after task. There was a main effect of environment complexity ($p = 0.003$) but a non-significant effect of task complexity ($p = 0.02$) on knowledge test scores after debriefing.

We performed a multivariate general linear model using task as the fixed factor for all five dependent variables to check for order effect. There were no significant effects, which indicates that the task order did not significantly affect any of the outcome variables. We also computed a multivariate general linear model using cluster (subgroup) as the fixed factor for all five dependent variables. There were no significant effects of clusters for performance score or cognitive load measures. However, there were significant effects on knowledge after the task ($p < 0.001$), and knowledge after debriefing was

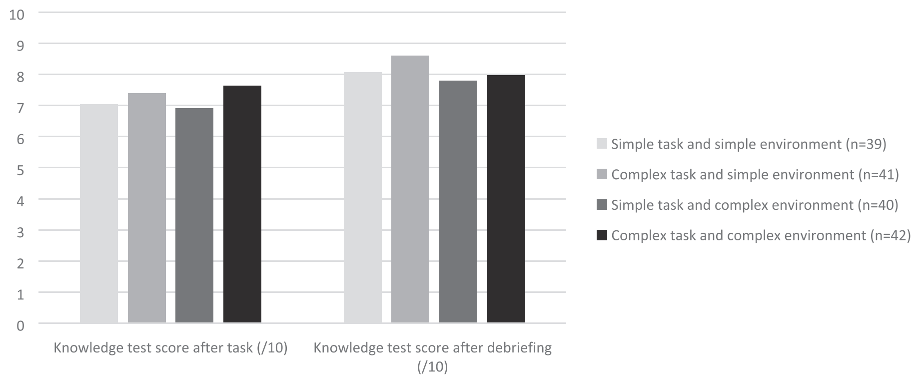

FIGURE 5 Impact of modulating task and environment complexity on students' mean results in knowledge tests (10 true or false questions) after simulation tasks and debriefing. Mean scores in simple environment were 7.1 (SD = 1.0) after simple task and 7.4 (SD = 1.5) after complex task. In complex environment, mean scores were 6.9 (SD = 1.2) after simple task and 7.6 (SD = 1.1) after complex task. No significant interaction effect between task complexity and environment complexity ($p = 0.34$). There was a main effect of task complexity ($p = 0.01$) and a non-significant main effect of environment complexity ($p = 0.79$) on knowledge test after task. Mean scores in simple environment were 8.1 (SD = 1.1) for simple task and 8.6 (SD = 0.7) for complex task. In complex environment, mean scores were 7.8 (*SD* = 1.1) for simple task and 8.0 (SD = 0.7) for complex task. No significant interaction effect between task complexity and environment complexity ($p = 0.27$). There was a main effect of environment complexity ($p = 0.003$) but a non-significant effect of task complexity ($p = 0.02$) on knowledge test scores after debriefing.

borderline significant ($p = 0.04$). Therefore, in this study, clusters did not significantly affect the majority of outcome variables, aside from knowledge after task and potentially knowledge after debriefing. We therefore refrained from interpreting knowledge after task with regard to modulation of complexity.

4 | DISCUSSION

In this study, we demonstrated that task and environment complexity interact with each other and impact novices' performance in simulation. Students' performance was surprisingly good, and cognitive load remained moderate in all conditions, which suggests that, despite increased complexity, students managed to learn from the simulations.

When struggling with the environment, students' focus seemed to shift from the task and was redirected towards managing the environment. As reflected by the effect of task complexity on intrinsic cognitive load, our students seem to strategically manage their own cognitive load—consciously or not—as complexity increases to ensure that they perform to a certain level and learn something relevant. This finding is in line with other studies that have described how the environment influences student learning in simulation.[2] However, although this strategy prevents students from experiencing cognitive overload, it might also impede their capacity to meet all the intended learning goals. Moreover, learning to deal with the environment while solving a clinical problem is inherent to simulation-based education[6] or authentic clinical work. To ensure that novices meet the learning goals in complex environments, educators could allow more time and more trials to practise complex tasks. This strategy has been proven effective to rapidly improve clinical performance of advanced learners.[23] Future research needs to confirm whether similar results can be obtained in complex environments for novices.

From a theoretical perspective, our findings reinforce the idea that environmental complexity is associated with intrinsic cognitive load. As postulated by Choi et al.,[4] the learning environment, which had mostly been depicted as a source of extraneous cognitive load in the past, acts as a distinct causal factor of intrinsic cognitive load by directly contributing to the learning goal and not only acting as a distraction. This finding is also in line with other exploratory work in clinical settings that force us to reconsider the role of the environment,[2,24] whether simulated or real, in the learning process.

4.1 | Limitations

The knowledge tests used to measure learning outcomes in this study might not fully capture the nature and depth of learning in simulation. True or false questions were mostly related to clinical knowledge and hardly targeted environmental features, partially explaining the lack of large differences between conditions. We also acknowledge that features from the task and the environment in simulation can be easily distinguished in theory but be difficult to discriminate in practice. Therefore increasing environment complexity might actually affect task complexity, which can partly explain the limited yet significant differences between conditions.

Although we modified a tool widely used in simulation-based education to assess performance, we could not find a large difference between conditions. This could be the result of a ceiling effect, which is often the case when using such instruments. This could also be because the anchors may be unadapted for novices. In our observations, we noticed that students were often not necessarily putting the patient at risk (i.e. score of 1) but not performing above standards (i.e. score of 4) either, leaving very little room for all the nuances there can be between degrees of performance. However, we could not find a tool in the literature appropriate for novices to assess the quality of their performance with all the nuances required.

4.2 | Conclusion

When designing simulation, the complexity of the task and environment can be increased without jeopardising novices' performance or creating cognitive overload. As complexity increases, novices' capacity to attend to the learning goals intended might be compromised. Educators could consider increasing the number of opportunities to practise with the same level of complexity to ensure that the learning goals are met.

ACKNOWLEDGEMENTS

The authors wish to thank Geneviève Lesage, pharmacist and educator, who acted as simulation instructor and performance rater in this study. We thank the staff of Centre Apprentiss who collaborated in simulation design and pilot testing. We thank Sarah Chiasson-Leblanc and Cecile Duval for helping with logistical aspects, Alexandre Lafleur for commenting on analyses and manuscripts and Mr. Douglas Michael Massing for copyediting the manuscript.

CONFLICT OF INTEREST

The authors have no conflict of interest regarding this study.

ETHICS STATEMENT

The project has received prior approval from the Research Ethics Committee of Laval University.

AUTHOR CONTRIBUTIONS

All authors contributed to its conception and approved the manuscript for submission.

PRIOR PUBLICATION OF THIS WORK

None.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Tremblay M-L, Rethans J-J, Dolmans D. Task complexity and cognitive load in simulation-based education: A randomised trial. *Med Educ*. 2022;1-9. doi:10.1111/medu.14941