Confidence drives exploration strategies in interactive simulations

Amaël Arguel
Department of Educational
Studies,
Macquarie University

Jason M. Lodge
Melbourne Centre for the Study of
Higher Education,
University of Melbourne

Mariya Pachman
Department of Educational
Studies,
Macquarie University

Paula G. De Barba
Melbourne Centre for the Study of
Higher Education,
University of Melbourne

Maximising the benefits of digital learning environments requires understanding how students process what they are exposed to in these environments. Besides approaches based on examining information processing within the cognitive domain, the importance of including emotions has been recently addressed. This study aimed to explore emotional dynamics during discovery learning in an interactive simulation, with continuous measures of self-reported confidence and challenge. Interactions from participants were recorded and two groups were created according to the exploration strategy used: systematic or non-systematic. Visual exploration was also measured by eye tracking as well as knowledge at pre- and post-test. Results suggest that learners using a systematic exploration strategy ran significantly more simulation cycles than non-systematic learners. Moreover, the latter group reported to be significantly less challenged and more confident about understanding the material. These results emphasise the importance of student perceptions of their capabilities when learning in flexible, less structured digital environments.

Keywords: discovery learning; confidence; interactive interface; digital learning environments

Discovery learning, confusion, challenge, and confidence

Although somewhat controversial in terms of efficacy, discovery-based learning environments provide opportunities for understanding how students learn when exposed to relatively unstructured learning environments. Discovery-based or simulation-based environments provide students with the ability to choose their own way through the learning process to a large extent. In digital learning environments, this is achieved by offering students flexibility in the environment. This flexibility can take many forms. Some environments are relatively constrained but give students some freedom to make choices about their path through the environment. Other environments, particularly immersive simulations (e.g., Kennedy, Ioannou, Zhou, Bailey, & O'Leary, 2013), are more flexible, giving students many options for choosing how they progress through and interact with the technology and with the content.

Discovery-based learning environments have been criticised due to a lack of direct instruction (Kirschner, Sweller, & Clark, 2006). Hattie and Yates (2013) for example, argue that students are often ill prepared to use these environments and struggle to make sense of the material within. In less structured learning environments, students are required to take more responsibility for their learning than in well structured ones. This means that students need to rely more on their use of self-regulatory skills and motivation in such environments, which may or may not be sufficient to support them (Graesser, McNamara, & VanLehn, 2005; Wigfield, Hoa, & Klauda, 2008). The opposing view is that, in making decisions about their own progress through the material, students are able to construct new knowledge based on their prior knowledge and experiences. Thus, discovery-based environments align well with constructivist theories of learning (e.g., Bruner, 1961). In the case of conceptual change, these discovery-based environments appear to be particularly beneficial. De Jong and Van Joolingen (1998) conducted a review of research focussed on discovery-based learning environments and found that virtual conceptual simulations can be particularly effective in bringing about conceptual change. Therefore, when students need to learn complex material, a discovery-based environment appears to be beneficial in allowing students to engage with the material in a more personalised way by giving them flexibility in their approach and progress. However, the uncertainty about the effectiveness of these approaches suggests that caution must be used in their application.

One affordance that is often overlooked in relation to discovery-based digital learning environments is that they also provide opportunities to uncover the process of learning. Much of what is understood about learning in the higher education context is reliant on theory or on student performance in assessment. Learning and performance are not the same thing (Soderstrom & Bjork, 2015). Performance is related to the production of an artefact of some description; a snapshot of student achievement. Learning, on the other hand, is a developmental process that occurs over time. Flexible learning environments not only allow students flexibility to personalise how they go about their own learning but the choice of strategies they use also provide clues as to how they are progressing and regulating their learning. Analysing these choices and strategies then allows for intervention if it appears that students are veering into unproductive learning behaviours. In other words, flexible learning environments provide an opportunity to better understand how students approach ill-structured learning and then use this information to enhance the design of the environment through iterative cycles (see also Bakharia et al., 2016).

Where the affordances provided by the ability to monitor and track student progress may be of most benefit is in building on the fledgling research to date about student emotion and subjective experience as they acquire knowledge. Traditionally, the information processing aspects of student learning have received more attention than subjective states and emotion (Pekrun & Linnenbrink-Garcia, 2014). It is becoming increasing apparent that these subjective states heavily influence whether students can successfully navigate through discovery-based environments. For example, a growing body of research demonstrates that, while student confusion can be beneficial in helping students achieve conceptual change, if it is not effectively resolved, students can experience boredom and frustration, which can lead to them giving up (Arguel & Lane, 2015; D'Mello & Graesser, 2014; D'Mello, Lehman, Pekrun, & Graesser, 2014). The detection of emotions, such as confusion, in digital learning environments can hence be a critical factor to maintain learners in an optimal emotional state promoting the best learning performances (Arguel, Lockyer, Lipp, Lodge, & Kennedy, in press). Early detection of learner confusion could be performed on the basis of analysis of visual exploration strategies measured with an eye tracker (Pachman, Arguel, Lockyer, Kennedy, & Lodge, in press). Therefore, the focus of the study discussed in this paper is on the subjective aspects of learning in digital environments. Our aim was to align these subjective states with the strategies used to navigate through the environment and the visual exploration of the learning material. In doing so, it was expected that a further link could be made between student learning strategies and the cognitive and affective states that drive these strategies.

One challenge that is particularly difficult in the development of better understanding about student experiences as they learn in discovery-based environments is the vast individual differences between students. Not only do students have differing levels of prior knowledge, they will adopt different strategies when learning. For example Dalgarno, Kennedy, and Bennett (2014) report that learners' exploration activity can be categorised into at least two types of strategies. In a comparison between scientific material presented in a tutorial style module and an interactive style module, Dalgarno et al. found that students tended to adopt either a systematic or non-systematic approach in the interactive version. The difference in this case is that systematic approaches tended to be more methodical, changing a limited number of variables in each simulation run compared to non-systematic approaches that involved a more haphazard strategy. The students adopting the systematic approach achieved greater learning gains than did either the tutorial condition or the students who adopted a non-systematic approach. In this instance, the individual differences in strategy selection had a significant effect on student learning. The strategies students adopt as they learn in these environments will be driven by their experiences and potentially other factors such as personality factors, motivation and interest in the material (Ames & Archer, 1988). In a follow up study, Lodge and Kennedy (2015) found that confidence was an important factor related to the strategies students adopt when exploring discovery-based environments. More confident students appear to have a tendency to overestimate their understanding and tend to be less systematic and methodical in their strategies. This aligns with work on overconfidence, in particular the Dunning Kruger effect (Kruger & Dunning, 1999) or the observation that the most unskilled are often unaware that they are in fact unskilled and tend to overestimate their skills or knowledge.

Understanding how the subjective experiences of students such as their confidence level relate to the other factors that influence how they use discovery-based environments is therefore an important issue for research in educational technology. Furthermore, being able to personalise and adapt the environment on the basis of the strategies students adopt will require determining how they are experiencing the learning environment and how this aligns with observable interaction with the task. Learning analytics and the learning sciences have begun to provide some clues about how different strategies used in discovery-based environments can be productive or non-productive. Our aim on this study was to take a further step towards connecting the student subjective experience of the task in terms of their level of confidence and perceived challenge and the observable interactions as they complete the task. Exploring the relationship between these factors is important if more sophisticated, adaptive systems are to be built that can respond to the student experience of the task. We did so in this study by assessing students self reported levels of confidence and perceived difficulty (i.e. how challenging) they felt the task was. This data was then compared and contrasted with two forms of observable behaviour that both give an indication of the strategy that students adopt. The first is the audit trail of activity in

the task (as per Dalgarno et al., 2014 and Lodge & Kennedy, 2015). The second was gaze tracking, as has been used extensively to determine how students process material in digital learning environments (Van Gog, 2007). The use of an eye tracker for measuring gaze trajectories was the novelty of our study compared with the previous studies using the same learning material (Dalgarno et al., 2014 and Lodge & Kennedy, 2015).

Experimental study

Material and method

Participants
Thirty-three participants were recruited from the Macquarie University campus. For technical reasons, the recording of eye tracking data failed for 4 participants. Consequently, these participants were removed from analyses and the sample size used in the study was finally of 29 participants. The study was advertised on the university internal career website and all participants were compensated of A\$15 for their participation. The age of participants varied from 18 to 29 years ($M = 21.79$, $SD = 2.85$) and the sample included 22 female participants and 7 males.

Materials
The learning material used in the study was initially developed for a study on discovery learning with computer-based simulations (Dalgarno et al., 2014) and has been subsequently used in another study (Lodge & Kennedy, 2015). The learning task was about understanding the influence of several factors on the level of the blood alcohol concentration and its evolution over time. The learning material consisted of an interactive interface displayed in a screen and composed of two panels (see Figure 1). On the left panel, seven parameters were manipulable, such as the body weight, the number of consumed standard drinks or the time when started to drink. On the right panel, a graph depicted the evolution of the blood alcohol concentration over a 24-hour period. Once participants were ready to observe the result of the manipulation of one or several parameter values, they clicked on a "Run Simulation" button and an updated curve was shown in the next screen. Running each simulation created different graphs and allowed participants to visualise the effect of the variables on the blood alcohol concentration, and also, to confirm or disprove some of their previous ideas triggered by the pre-test.
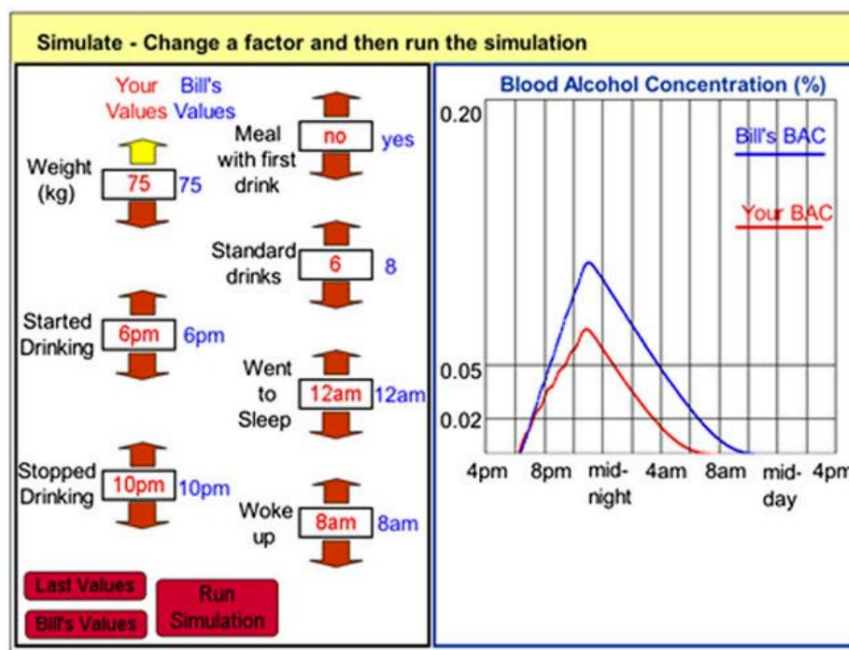

Figure 1: Screenshot of the simulation interface

Visual exploration of the material was recorded with an eye tracker Tobii T120 capturing participant's gaze at a frequency rate of 60 Hz. This eye tracker system is based on a non-invasive technology using infrared remote cameras and did not require the immobilisation of participants' head or the wearing of a head-mounted device. Interaction data (e.g., mouse pointer locations and click events) were also recorded and serve as an indicator for the classification of participants into the systematic and non-systematic groups.

Procedure

Before starting the learning task, all participants completed a paper-based pre-test questionnaire in order to assess their initial knowledge on the blood alcohol concentration mechanisms. Then, an experimenter calibrated the eye tracker for each participant before they started to navigate autonomously through a series of pages displayed on the eye tracker built-in screen (17" TFT, 1280x1024 pixels). At the bottom of each page, an actionable button "next" was available to access the next page. The eight first pages provided participants with the instructions, an introduction paragraph to the topic, and a practice activity. The following pages were the simulation runs. After each page, participants were asked to rate on paper-based scales their level of confidence about the material and how challenging they found the material to be. These were simple visual analogue scales from 0 – 10 with anchor points ranging from not at all to very much so (as per Lodge & Kennedy, 2015). Participants had the possibility to perform as many simulation runs as they wanted until they thought they had understood the material sufficiently. Finally, a post-test questionnaire was given to participants to assess their level of knowledge and to collect some demographics. Some questions were used to evaluate general motivation and study habits were given to participants. These questions were adapted from previous research and notably from the Motivated Strategies for Learning Questionnaire (MSLQ) (Elliot & McGregor, 2001; Hulleman, 2007; Pintrich & De Groot, 1990). This combination of items has been previously used in digital learning environments with undergraduate students and reported acceptable reliability (de Barba, Kennedy, & Ainley, 2016). Constructs measured included value beliefs, individual interest, goal orientation, self-efficacy, control beliefs, metacognition, elaboration, organisation, effort regulation, peer learning, help-seeking behaviour, and study environment and time management.

Results

Interaction patterns with the simulation

The data gathered from the simulation indicated differences in the way that participants were interacting with it. Some participants manipulated only one parameter at each cycle of simulation, whereas others preferred to change values of several variables before to run each cycle of the simulation. This variability of behaviours is interpreted as being the touchstone of the different strategies participants employed. Consequently, we have classified participants either as systematic or as non-systematic explorers, in a similar way as in Dalgarno et al. (2014). Systematic participants were defined as exploring the simulation by changing the value of only one parameter between each simulation run, on four or more occasions. This threshold was chosen according to Dalgarno et al.'s study, in which it was stated that the value of four could be considered as the minimum number of systematic iterations needed to learn key concepts of this learning material. In contrast, all other participants are classified as non-systematic explorers. According to this classification scheme, the sample of the study is composed of 20 systematic and 9 non-systematic explorers.

Number of simulation runs

During the learning task, participants were able to stop the discovery activity with the simulator at any time, which is as soon as they thought to have sufficiently understood the learning material. The total number of simulation runs before stopping varied from 5 to 26 runs ($M = 11.6$, $SD = 5.72$). There was an observable difference in the number of simulation runs performed between the groups. As illustrated in Figure 2, the participants from the non-systematic group ran on average a smaller number of simulation cycles ($M = 6.11$, $SD = 0.6$) than participants from the systematic group ($M = 14.1$, $SD = 5.23$). A Mann-Whitney test showed that this difference was statistically significant ($U = 9$, $p = .0001$), producing an effect size of $r = 0.9$ (Wendt, 1972).
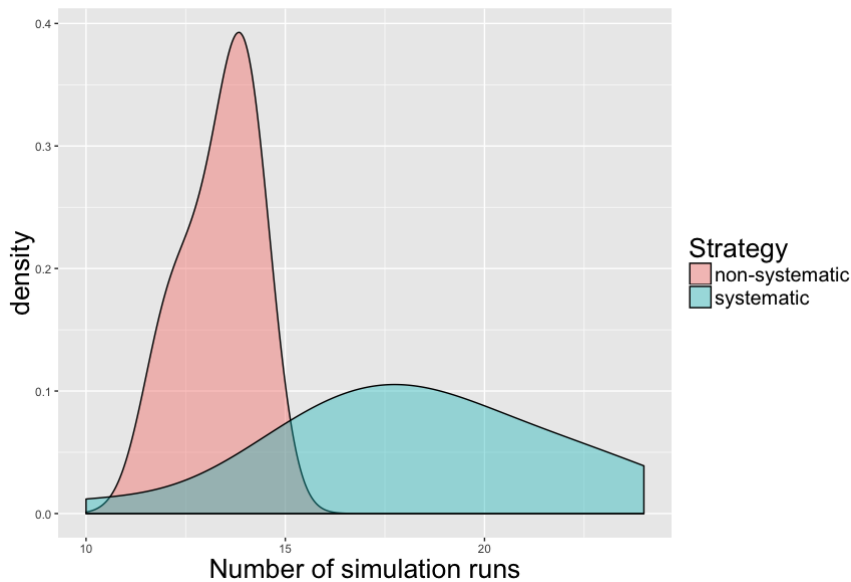
Figure 2: Estimated density of the number of simulation runs, according to the exploration strategy

Time spent on each simulation run

As well as for the number of simulation runs, participants were free to spend as much time they wanted in working on each of the runs. Despite the participants belonging to the systematic group performed more numerous simulation cycles, the time they spent on each cycle ($M = 59300$ ms, $SD = 36600$) was not significantly different from the time spent by the participants of the non-systematic group ($M = 62100$ ms, $SD = 32800$), $U = 4511$, $p = .4$. The distribution of the amount of time spent per simulation run according to the exploration strategy is presented in Figure 3.
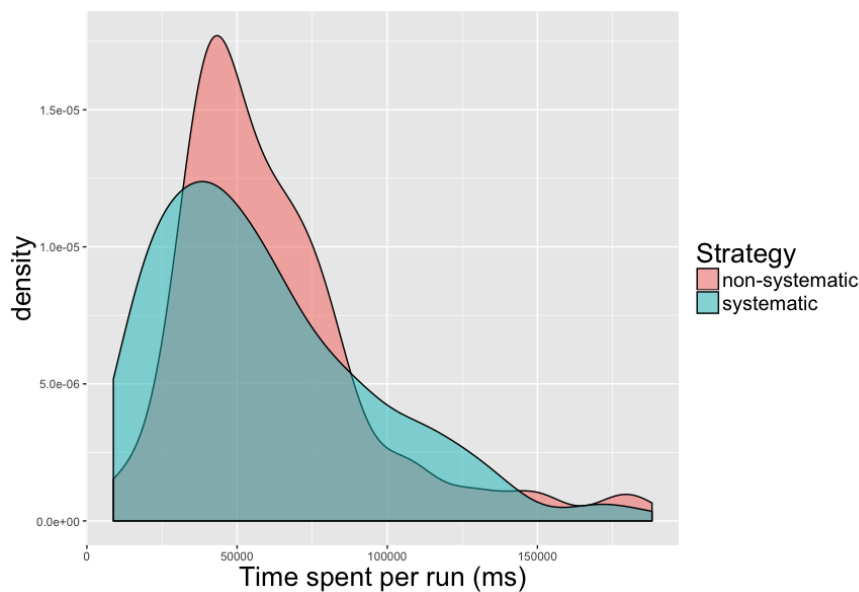
Figure 3: Estimated density of time spent in each simulation run, according to the exploration strategy

Visual exploration of the learning environment

During the entire learning task with the simulator, an eye tracker recorded the gaze trajectories and fixations from participants. However, analyses of data did not reveal any differences between the systematic and the non-systematic groups for visual exploration patterns. Figure 4 shows a representation of the simulator interface with additional layers depicting in different colours the areas of interest used for analysis and an example of heat map representation of additive gaze fixations on several locations of the screen. Red coloured areas represent zones of the screen with a higher number of fixations and denote locations attracting high levels of visual attention or a cognitive processing.
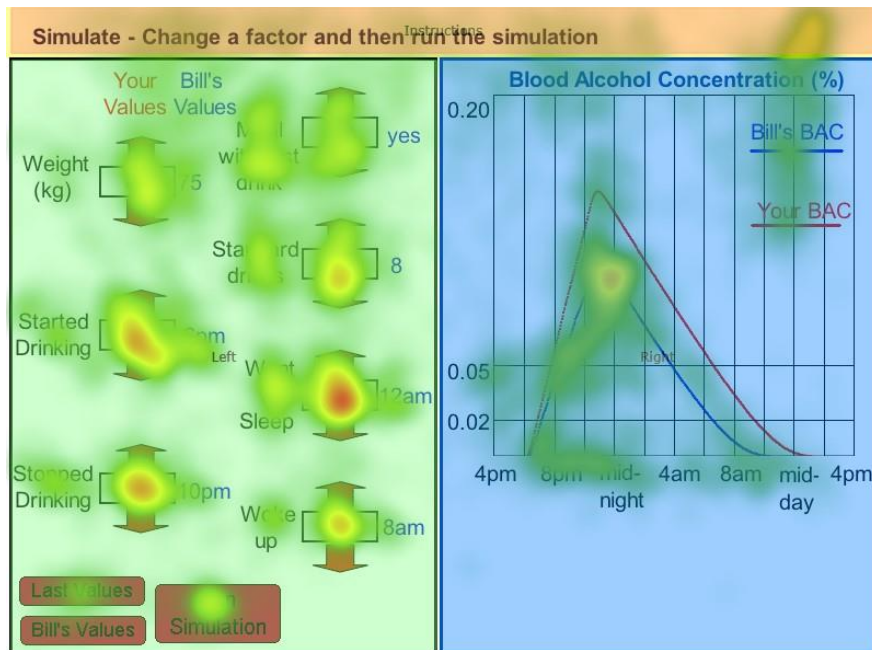
Figure 4: Visualisation of the simulation interface with heat map representation of gaze fixations

Responses to the questionnaires

General motivation and study habits questionnaire
No significant differences were observed between the groups of participants for any of the dimensions of the general motivation and study habits questionnaire. An explanation of the absence of differences here might be found in the nature of the items. Indeed, most of the questions asked of participants were quite general, addressing their course level learning experience rather than the task level learning experience that participants were subjected to in the study. Because the sample was composed of homogeneous participants, all being undergraduate university students, it is not surprising that only non-significant differences are observed regarding the responses given to generic questions about motivation and study habits.

Learning performances
According to the knowledge scores produced at pre- and post-test, all participants performed better after the completion of the simulation, Wilks' $\lambda = .57$; $F(1,27) = 20.48$, $p < .001$. But, there was no significant difference between the learning performance gains of systematic and non-systematic groups, Wilks' $\lambda = .99$; $F(1,27) < 1$. Consequently, we are not able to observe any significant differences of learning performances according to the exploration strategies used by participants.

Questionnaires about the session
Measures of emotions did not reveal significant differences between the systematic and the non-systematic groups either, except for the rating of Frustration. Participants from the systematic group agreed significantly more with the statement "I found this activity frustrating" ($M = 2.30$, $SD = 1.49$) than participants from the non-systematic group did ($M = 1.33$, $SD = 1.00$), $t (22.5) = 2.05$, $p = .05$ (adjusted test for not equal variances).

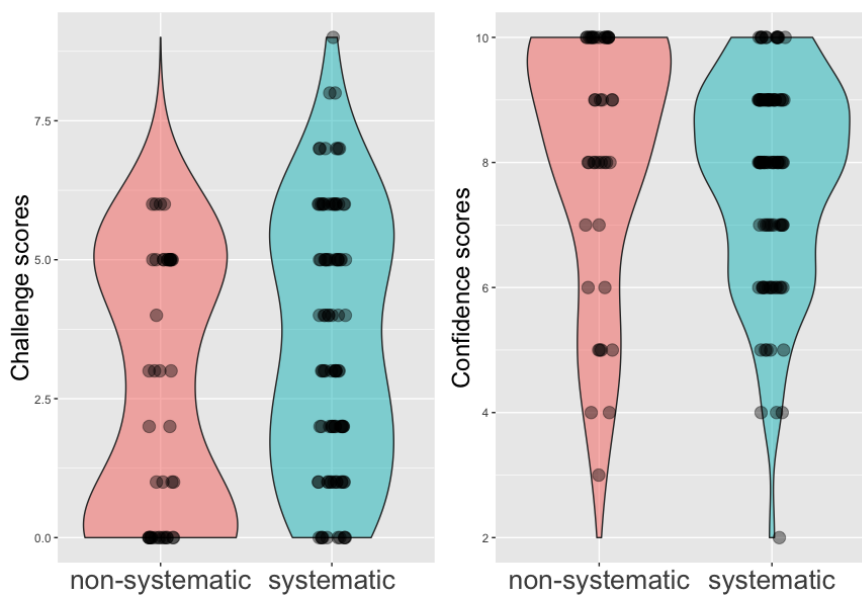*Self-reported scores of Challenge and Confidence*
After having completed each run on the simulator, participants were asked to report on paper-based scales (from 0 to 10) as for how confident they were feeling regarding the understanding of the material (Confidence score) and how challenging they thought the material was (Challenge score). A previous study based on the same learning material found that the ratings of these scales were negatively correlated with each other (Lodge & Kennedy, 2015). A similar pattern has been also observed in our study (see Figure 5).
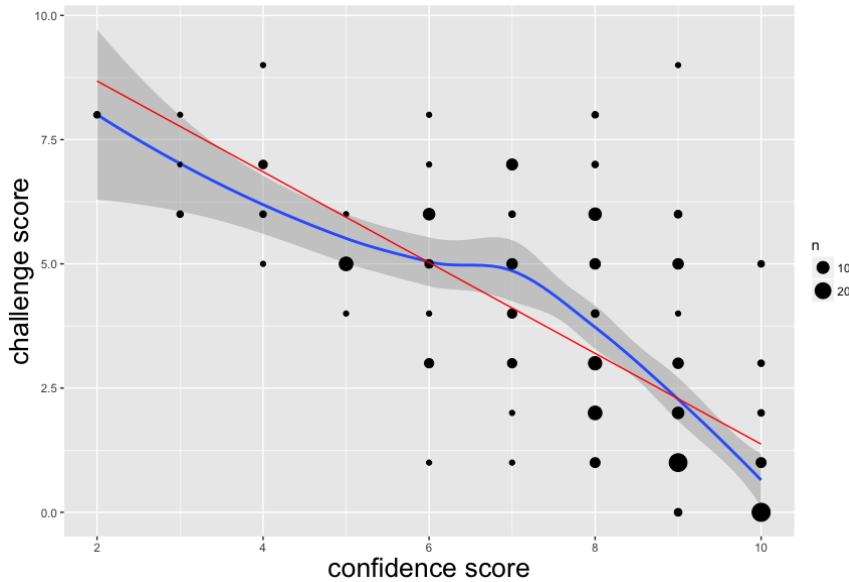
Figure 5: Relationship between Challenge scores and Confidence scores (for all participants and all simulation runs)

The observation of the relationship between scores for Confidence and for Challenge shows a significant negative correlation, $r(235) = -0.68$, $p < .001$. This result provides evidence that these two dimensions are perceived as having an opposite meaning from the participant point of view.

Because participants were able to stop the learning task as soon as they believed having sufficiently learned from the simulation, only the first 5 runs of simulation were common for all the participants. For this reason, to examine differences of rating between the groups, only the first 5 runs were considered, as shown in Figure 6.

Figure 6: Estimated density of the scores reported for Challenge and Confidence in the first five simulation runs, according to the exploration strategy

The analysis of results permitted to observe a significant difference of ratings between the groups. Indeed, a Mann-Whitney test indicated that learners who had adopted a systematic strategy for exploring the simulation reported significantly higher Challenge scores ($M = 3.54$, $SD = 2.34$) than non-systematic participants ($M = 2.57$, $SD = 2.37$), $U = 1489$, $p = .02$, although the effect size can be qualified as small ($r = 0.24$). In the same way, systematic learners also reported lower Confidence scores ($M = 7.73$, $SD = 1.68$) than non-systematic learners ($M = 8.17$, $SD = 2.05$), $U = 2368$, $p = .05$ with a small effect size ($r = 0.19$).

Discussion

In our study, the strategies that participants used for interacting with the simulation had not produced any observable effects on learning performances or on visual exploration patterns. However, the participants who chose to explore the simulation in a systematic way, by manipulating a limited number of parameters before they ran the simulation, required a significantly larger number of simulation cycles than participants who used the non-systematic strategy. This result is understandable because seven parameters were included in the simulation interface and the systematic participants were determined in this study by their tendency to manipulate only one parameter at each cycle of simulation. Consequently, in order to explore the majority of these parameters, systematic participants may have required a larger number of runs than non-systematic participants, who were testing the effects of several parameters simultaneously. Alternatively, learners who are higher in confidence adopt a non-systematic approach, which suggests that they could be overestimating their level of understanding and conduct less simulation runs due to overconfidence.

Surprisingly, despite of a larger number of parameters manipulated, the time spent on average in each simulation cycle was not statistically different according to the strategy used. It was expected that learners from the non-systematic group spent more time in each cycle since they were modifying several parameters, but also needed to understand the outcome of the simulation in relation to the effects of the manipulated variables. This situation was expected to be more difficult than understanding of the effect of a single variable on the blood alcohol concentration curves; hence it should have taken more time for processing the information. However, despite the supposedly greater difficulty of learning the material with a non-systematic strategy for exploring the simulation, no difference in terms of learning performance was observed in the study between the groups. Again, this suggests that participants in the non-systematic group may have been overconfident and were therefore only processing the task at a surface level rather than more slowly and methodologically as those in the systematic group did. Either way, this study failed to replicate the results of the initial study using the same learning material, which had provided evidence of the benefits in terms of learning performances of using a systematic exploration strategy (Dalgarno et al., 2014). However, our study provides an additional result with the observation of some relations between the exploration strategy and the learners' confidence or overconfidence.

Future directions

This study provides insightful results regarding the links existing between levels of confidence, feeling of challenge, and the type of self-exploration strategy used during a learning task consisting of the interaction with a simulation. Future research will be useful to determine the existence of a directional effect between these factors. As with any research, the present study presents some limitations, such as the small sample size and unbalanced group sizes, which is justified due to its exploratory design.

To know if the choice of a strategy depends on how confident a learner feels regarding a task, or alternatively if the use of a specific strategy influences the way learners rate their feelings, a randomised controlled methodology would be needed. It is also possible that the individual differences of personality of participants may be a determining factor. For example, cautious learners might present a general tendency to use a systematic approach in exploring the simulation and also rate somewhat low their level of confidence, whereas more adventuresome learners would be quite overconfident, adopting a non-systematic exploration strategy. The latter case might also be related to an *illusion of understanding* experienced by some learners with a low prior-knowledge of the domain (Pachman, Arguel, & Lockyer, 2015). A frequent occurrence of an illusion of understanding in multimedia learning environments makes this explanation quite plausible (Paik & Schraw, 2013). Nevertheless, this would not completely explain the underlying mechanisms that can lead to benefits in learning performances. It is likely that more than one factor has an impact on the learning gains of the participants.

In Dalgarno et al.'s study (2014), participants had the possibility to explore the simulation in a systematic or a non-systematic manner, but they also had the opportunity to continue working on the learning task as long as they needed before feeling sufficiently confident about the topic learned. For this reason, it is possible that participants who were particularly confident believed to have sufficiently understood the material earlier than less confident participants, and did consequently run a smaller number of simulation cycles. If, like in our study, the amounts of time spent on each simulation cycle were similar for all the participants, it is also plausible that the total exposure time to the learning material would be different among learners. Since the most confident participants would have adopted a non-systematic approach, spending less overall time learning the material, they eventually produced lower learning gains than the less confident participants, which would have invested more time on the learning task. Nevertheless, neither the number of simulation cycles used nor the time spent on each of them was controlled for the exploration learning condition in the Dalgarno et al.'s study, hence the

explanation provided here remains purely speculative. It however illustrates the complexity of drawing an algorithm of learning performances when inputs such as differentials between learners' behaviours, self-judgements of learning and feelings are involved.

To conclude, the approach consisting of including learners' individualities on their experience of feelings such as confidence and challenge, is a promising approach to improve the design of discovery-based digital learning environments. According to the results observed in our study, it is likely that the level of confidence and the self-discovery strategies are indeed linked. These strategies were operationalized in our study by a logical distinction we made between systematic and non-systematic learners. This distinction was certainly not the only one we could have chosen to differentiate different types of self-discovery strategies. Each learning situation, for which a specific instructional content is delivered in an environment, possesses its own specificities that educators may need to consider for improving learning outcomes. The present study provides a useful clue by pointing toward the direction of a relationship between emotions and self-discovery strategies captured by individual interaction patterns with the digital learning environment. Of course, knowledge about this effect is emergent and it needs to be developed with more studies and also from the experience of educators in their practice of teaching.

Acknowledgments

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