Factors affecting student behavioural engagement in an inquiry-based online learning environment

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Abstract

The technological innovations and changing learning environments are influencing student engagement more than ever before. These changing learning environments are affecting the constructs of student behavioural engagement in the online environment and require scrutiny to determine how to facilitate better student learning outcomes. Specifically, the recent literature is lacking in providing insights into how students engage and interact with online content in the self-regulated environment, considering the absence of direct teacher support. This paper investigates how instructional design, informed by the factors relating to behavioural engagement, can influence the student-content interaction process within the fabric of inquiry-based learning activities. Two online learning modules on introductory science topics were developed to facilitate students' independent study in an asynchronous online environment. The study revealed that students showed high commitment to engage and complete the tasks that required less manipulative, pro-active effort during the learning process. The findings also revealed that instructional guidance significantly improved the behavioural engagement for student groups with prior learning experience and technology skills. This study highlights several issues concerning student engagement in a self-directed online learning environment and offers possible suggestions for improvement. The findings might contribute to informing the practice of teachers and educators in developing online science modules applicable to inquiry-based learning.

1. Introduction

Student engagement is a prerequisite for learning and central to any successful educational experience. Contemporary research relating to online learning environments (Garrison & Cleveland-Innes, 2005; Meyer, 2014) highlights the key role of engagement for effective learning. Researchers have endeavoured to define and understand various dimensions of student engagement that apply across various contexts (Bond et al., 2020). Some have defined student engagement as a 'psychological process' implicated in learning (Marks, 2000); others have conceptualised it by considering what behaviours count as engagement (Harris, 2008) and what constructs need to be considered to define them (Sinatra et al., 2015). Nonetheless, commonly identified and investigated dimensions of engagement found in the literature focus on the behavioural, cognitive, and emotional aspects of this phenomenon (Fredricks et al., 2004). Behavioural, cognitive, and emotional engagement often include multidimensional constructs and are highly influenced by context and defined by a given conceptual framework (Reeve et al., 2019; Schmidt et al., 2018). Whether it is the construct or context, it has been argued that a detailed level of specificity is required to measure and conceptualize student engagement (Sinatra et al., 2015).

Within an online learning context, student engagement and interactivity are difficult to capture in precise detail (Rojas et al., 2016). One of the reasons for this difficulty resides in the complex nature of the online environment and the nature of the task involved. The online environment may involve multiple dimensions as variables (figure 1) and their combination requires careful consideration during instructional design.

A traditional didactic lecture might be defined by combining the far, left-hand conditions in the continua in *figure 1*, whereas an online, open, inquiry-based learning environment involving individual students might be described by a combination of the far right-hand conditions. Mayer (2004) presents a strong case for avoiding unstructured, unguided inquiry environments where high cognitive load and lack of direction may result in negative outcomes on student learning.

Online students in remote, asynchronous, individual environments are likely to experience different interactions to those in face-to-face, teacher facilitated, synchronous contexts (such as the traditional classroom), immediate individual feedback is easier to deliver in the latter. Also, an online environment offers a novel teaching and learning context which is highly influenced by the digital interface, available technologies, and the underpinning pedagogical design. Mayer (2019) proposes, after 30 years of research on online learning that the instructional methods are central to student learning and are informed by a combination of behaviourist, cognitivist, and constructivist conceptions of learning. It is not the instructional media on its own that enables learning.

Key questions that educators might pose regarding students' engagement in online contexts include: *What do students engage with? When do students engage?* and *How do students use educational technology in their learning?* (Ding et al., 2017; Dixson et al., 2017; Sheeran & Cummings, 2018). To answer these questions, educational institutions are primarily dependent on the data from the learning management system (LMS) analytics. LMS analytics readily capture quantitative engagement data such as how many clicks, login time, submissions or reads were made by each student. Total time spent on the activities, the total number of completed tasks achieved, etc. are also available in LMS. However, while data analytics are conceptualised as indicators of student behavioural engagement, they are insufficient to define student engagement in detail, specifically the quality of the engagement related to learning. Researchers are keen to understand the nature of students' engagement with the technology resources while they study independently and how the underlying pedagogical design influences students' independent interactions during tasks. To address this issue, the following research question has been investigated within an inquiry-based learning context to enable further understanding of the nature of student exploration and interaction with the learning content:

What factors influence student behavioural engagement during their interactions with online content as part of a self-directed learning environment?

2. Behavioural Engagement In The Online Context

Moore (1989) proposed three important interactions for online learning environments: student-content (S-C), student-teacher (S-T), and student-student (S-S) interaction. Moore's categorization has become a widely accepted framework for the study of the interrelationships between teacher, student, and content in an online environment. Student behavioural engagement inherently plays a key role in the effectiveness of these relationships.

In a traditional environment, it is conceptualized that the study of behavioural engagement relies on observation of student responses to physical and verbal cues provided by the teacher; however, these cues become less valuable in the online environment where students do not necessarily engage directly with their teachers and peers as part of the learning process (Lei et al., 2019). In an asynchronous online context, S-C interactions becomes the key indicator of student behavioural engagement. While visual indicators of physical engagement in the online learning process are not as evident as the face-to-face learning (Lei et al., 2019), Vytasek et. al, (2020) infer that tracking students' digital artefacts can be used to indirectly understand their behavioural patterns. However, these analytics data often provide insufficient information to understand how students intrinsically regulate their behaviour or why they behave in a particular way during the S-C interaction.

In the online context, student behavioural engagement can be transacted either in an individual study space or one that is socially oriented. Common examples of learning activities where students need to engage individually include self-contained online modules or courses designed for self-directed study. In contrast, students might engage more socially in their learning process to communicate with their teachers and peers by seeking help from them using feedback and forum features of learning management system (Baragash & Al-Samarraie, 2018). This mode of interaction creates social presence within technology-mediated contexts. Hong et al. (2019) argued that social presence demands active participation from the people involved in the online community. Research indicates that during collaborative tasks, students display interdependency and essentially synchronize their work through some level of time commitment (Romero & Lambropoulos, 2011; Yoo & Alavi, 2001). Furthermore, Yoo and Alavi (2001) found that group cohesion promoted students' drive to be involved in collaborative tasks, however this commitment is only possible when collaborative options are included in the online environment. In contrast, it is much more difficult to facilitate student engagement in an independent study space when no social interaction and collaborative tasks are available.

To better understand student behavioural engagement in the context of an online study environment without synchronous teacher (S-T) or peer (S-S) interactions, it is important to explore the nature of the student-content (S-C) interactions. Two primary aspects of online S-C interactions that have been explored in research are: *a)* total time spent (time-on-task) on the activity, and *b)* quality time spent (nature of student participation) in the learning process (Christenson et al., 2008; Ding et al., 2017). In their study, Brenner et al. (2017) considered both participation (such as the productive moves, clicks, total tries) as well as time on task (such as total elapsed time) to determine the students' behavioural engagement. Also, Romero and Barberà (2011) argued that both time-on-task and the quality of time spent could influence students' academic performance. Therefore, in this study, we combine both time-on-task and quality time spent (or participation) on the tasks to conceptualize students' behavioural engagement (see *figure 2*) during S-C interaction.

Previous studies have argued that a number of key behavioural engagement constructs need to be considered to understand student quality time spent in an online activity. For example, Young (2010) reported that the general indicators for behavioural engagement are when students demonstrate high effort and persistence in their learning. Fredricks et al., (2004, 2016), focused on effort, persistence, attention, positive conduct, and the absence of disruptive conduct in understanding student behavioural engagement. However, in online remote learning context, it is clearly more difficult to directly measure students' positive and disruptive conduct. Fredricks et al., (2004) reported that students' completion of a designated task is the sign of behavioural engagement. Additionally, a systematic and organised interaction process essentially provides a qualitative dimension to student engagement (Garrison & Cleveland-Innes, 2005). Therefore, in this study, students' systematic efforts in the inquiry process are conceptualised as 'systematic investigation' and considered as one of the important constructs to measure students' quality time spent on a task. In brief, the three important constructs that can define quality time spent by a student on a task are: persistence, systematic investigation, and task accomplishment (figure 2).

3. Instructional Method Design

Successful online learning cannot be demonstrated by behavioural observations alone, students need to be observed during the process of actively constructing their understanding through instructional methods that support cognitive processing during learning (Mayer, 2019). Inquiry-based learning environments have gained considerable attention from science educators due to the reported benefits they offer in achieving enhanced cognitive outcomes (Donnelly et al., 2014), and problem-solving skills (Gillies et al., 2013) for students. Nonetheless, educators have often found it difficult to successfully engage students in the inquiry process online, specifically for those students who require careful guidance during the learning process (D'Angelo et al., 2014; Sergis et al., 2019). Critically, it has been found that students have demonstrated poor participation when scaffolding or guidance has been absent during online learning (Tallent-Runnels et al., 2006). Therefore, educators are continually seeking a viable solution to delivering an effective, guided inquiry-based, online learning environment. In recent times, sophisticated technology has offered educators the opportunity to explore and create more sophisticated guided learning environments (Hong et al., 2019). However, Meyer (2014) recommended that a strong pedagogical design is required to create and structure the learning environment that makes what they need to do and achieve transparent for students.

The inquiry-based learning environment is exploratory by nature in science education, it requires active participation, and self-regulation by students in the process of their knowledge construction (Sharples et al., 2015). Therefore, students are encouraged to engage in a series of inquiry cycles formulating their own reasoning on the problem under investigation during the process (Pedaste et al., 2015). In creating an effective pedagogical design, educators often categorise the student learning process in accord with the cycle of inquiry phases. One of the popular long-standing pedagogical strategies employed within science education is the *predict observe explain* (POE) pedagogical framework (White & Gunstone, 1992). The POE pedagogical framework supports instructional methods that enable students to work in phases. For example, students need to predict a phenomenon, perform an observation, then explain the observed findings in relation to the initial prediction (Bilen et al., 2016). Other studies have also reported that the POE framework can be used to change the students' initial misconceptions into correct ones (Ayvacı, 2013; Karamustafaoğlu & Mamlok-Naaman, 2015; Samsudin & Efendi, 2019), while supporting self-regulation (blinded) in the inquiry process.

Consequently, the *predict, observe, explain, and evaluate* (POEE) pedagogical design, an extended version of POE, has been utilised in this study to provide a series of inquiry phases for student learning in an asynchronous, self-directed, online environment. The details of the development of this pedagogical design have been reported elsewhere (blinded). *Figure 3* shows the schematic representation of the POEE pedagogical framework.

Under the POEE pedagogical design, emerging technologies such as interactive multimedia have been employed to promote higher quality S-C interactivity in terms of elicitation, exploration, explanation, and clarification of the concepts. Such multimodal technology, including dynamic and interactive representations, may help students to understand more complex science concepts (Bernard et al., 2009) and support increased student performance (Mayer et al., 2001).

In this study, the applicability of the POEE framework to guide instructional design for online inquiry-based environments has been demonstrated in the context of two learning modules that address the introductory science topics of *Phase change* and *Heat*. Several POEE activities have been employed in each of the learning modules and examples are shared in (blinded). Interactive simulations have been selected for inclusion in this study from two popular websites that share science simulations, namely PhET (https://phet.colorado.edu/) and Molecular Workbench (MW, http://mw.concord.org/modeler/). Additional media in the form of videos and animations were also utilised to introduce dynamic representations of concepts linked to text and embedded images. Such forms of technology integration in the online space can facilitate proximity between learners, teachers and learning contents and can influence student engagement (Dyer et al., 2018). In addition, Miles, Mensinga, and Zuchowski (2018) argue that delivering educational materials in multiple forms can facilitate student engagement, support effective navigation and utilisation of the materials.

4. Methods

4.1 Study context and participants

This study aimed to explore S-C interactions in a self-directed online environment and employ a mixed method research design. A group of 30 science students, enrolled in the first-year chemistry of a large Australian university were selected as a sample for this study. Due to the ease of access, this study employed a convenience sampling technique to secure this cohort. An invitation to participate in the study was distributed to all enrolled students through the LMS (Blackboard) and only those who expressed interest in participating in the study were recruited. The processes of data collection, analysis and storage used in this study have been approved through the institutional ethics committee and participation required students to opt in based on informed consent. Two student groups were formed based on their self-reported prior online experience: experienced and non-experienced. Prior online experience, in this study, was conceptualised as the student having experience of educational simulation in the online environment during their previous science learning. *Figure 4* summarises the details of the participants and study context.

The two learning modules were offered students in parallel to their formal courses, that is, these were not required for their courses. Students participated voluntarily in learning from the modules and they were aware that their performances would not be assessed; no grading was assigned to course marks upon their completion of a module.

4.2 Data collection

Observations of the S-C interactions included video recording, observation, and stimulated recall interview and a variety of tools were used to collect the data. Students were required to participate in only one of the two learning modules (either *Phase Change* or *Heat*) and participant IDs are formulated to indicate which module they had completed. For example, an ID that begins ‘pxxx’ indicates the *Phase Change* module and those beginning ‘hxxx’ indicate completion of the *Heat* module. At the beginning of the module, a short orientation was provided to the students showing different components of the web-based learning module such as the simulation models, videos, and other important elements. Each student was then left to work independently on their own in a dedicated room. The student’s on-screen computer activities were recorded through the Echo360 platform. Additionally, the researcher made observation notes on a student’s responses and on-screen interactions from a remote location using Virtual Networking Computing (VNC). Once a student finished a module, a stimulated recall interview was conducted to record the student’s immediate reflection on their experiences with the module (O’Brien, 1993). The video recording and the researcher’s notes on the students’ activities in combination provided the basis for conducting this post-module interview. These data collection techniques focussed on exploring the different constructs of behavioural engagement like persistence, systematic investigation, and task accomplishment.

4.3 Data analysis

This study used both an inductive and theory driven thematic analysis approach to formulate themes from the data (Boyatzis, 1998; Braun & Clarke, 2006). The constructs of behavioural engagement originated in the relevant theories (described above) while various sources documented in the literature review provided the basis of a rationale for formulating the construction of the themes. Thereafter, the students’ behavioural efforts, related to the identified themes, were quantified, and codified to measure the relative degree of influence those factors exerted on the interaction process. *Table 1* summarises the themes that emerged and related stratification in coding:

Table 1: Data analysis codebook

Themes	Effort indicators	Codification	Data Source
Time on Task	• Length of time	High/ Moderate/ Low	Video record, observation
Persistence	• Total length of time • Use of hints and concept check buttons embedded within the activities • Following instructions • Attempts to use most of apparatus and buttons embedded in the simulation model, • Taking snapshots (a feature in the simulation model)	High/ Low	Video record, observations, post-module interview
Systematic Investigation	• Structured Exploration • Understanding the functions of simulation parameters • Identification of the intended concept • Responding to question prompts • Prolonged exploration on the specific concept • Revisit the simulation model where necessary • Identification of the new concepts	Number of concepts investigated	Video record, observations, post-module interview
Task Accomplishment	See *table 3*	Complete/ Incomplete	Video record, observations,

Persistence is defined in the literature as a student's continuous effort to overcome various challenges faced in the process of learning (Parker, 2003). Likewise, student persistence, in this study, refers to the student's prolonged exploration with the simulation task in pursuit of understanding the science concepts, even though the consequences of this exploration might not contribute to their anticipated learning. In contrast, systematic investigation denotes a strategic and organised investigation of a concept, contributing directly to achieving the anticipated learning. Finally, in combining the results of both the persistence and systematic investigation, students' task accomplishment was assigned as either complete or incomplete. The codified data were then triangulated to explore how they impacted on students' behavioural engagement. *Table 2* further shows how the task accomplishment has been measured in terms of students' behavioural effort on persistence and systematic investigation.

Table 2*: Measurement of students' task accomplishment

MERs	Students' demonstration		Task completion
	Persistence	*Systematic Investigation*	
Simulation activities	Low	0 concept	Incomplete
	Low	1 concept	Incomplete
	Low	2 concepts	Complete
	High	0 concept	Incomplete
	High	1 concept	Complete
	High	2 concepts	Complete
Video activities	-Students see the full-length video without skipping any part.		Complete
	-Students did not engage and see the full-length video		Incomplete
	-Skipping some portion of the video		Incomplete
Open Response (Inquiry questions activities)	(Three criteria are considered in determining the task as 'complete') -Students correctly addressed the concepts -Students attempted to explain the reasons. It does not necessarily mean a correct explanation was provided. -Students attempted to explain it in molecular terms		Complete/ Incomplete

**Source:* (blinded)

After doing the thematic analysis and quantification of the themes, relevant statistical analysis has been conducted to get detail understanding of the data. An independent sample *t-test* has been conducted to consider whether any observed difference in mean engagement time between the experience and inexperience student groups was significant. Pearson's *chi-square* test of independence was conducted to gain further insight into any significant association between two categorical variables. A cross tabulation of the data has been formulated based on the observed value and the expected value coming from the null hypothesis, i.e., when the distribution is independent to each categorical variable. Research suggests that chi-square test can be conducted when expected values of the contingency table cells are greater than 5 (Franke et al., 2012). For any significant association between the categories in a *chi-squar*e test larger than 2 x 2 contingency table, *Cramer's V* has been reported to indicate the strength of the association (Kline, 2013). A value of *Cramer's V* less than 0.26 is considered to indicate weak strength of association (McHugh, 2012). Also, for a contingency table larger than 2x2, the source of a statistically significant result can be unclear. Therefore, a *post hoc* test is required to reveal where the significant result is existing in the contingency table cells (Sharpe, 2015). For this, *adjusted residual,* a recommended procedure compared to *other post hoc alternatives* has been used (MacDonald & Gardner, 2000). MacDonald and Gardner (2000) also suggested a Bonferroni correction in this process to reduce the chance of committing type 1 error. Therefore, this study used the Bonferroni correction to report the adjusted p-value for identifying the value which is statistically significantly different from the expectation of the null hypothesis.

Furthermore, when the number of observations was found small and the expected frequency in any cell of the contingency table was less than 5, a more appropriate form of analysis *Fisher's Exact* test has been utilised (Cochran, 1952). Research proved that to deal with small observation, *Fisher's Exact* test is particularly useful (Bower, 2003). This study combined the categories to form a 2x2 contingency table for

Fisher's Exact test. For 2x2 contingency table *Phi* value has been reported to indicate the strength of the association between the categories (Franke et al., 2012). All the statistical analyses were performed using SPSS with the significant p-value threshold set at 0.05.

5. Results

5.1 Engagement time with the learning tasks

It was estimated by the researchers that the standard time for a student to complete each module would be 50 minutes. Despite the absence of direct or personal guidance, student engagement time with the learning modules was found to be satisfactory. The average engagement time expended ranged from 44 minutes to 52 minutes for each learning module for both the experienced and inexperienced student groups. *Table 3* displays the statistics of student engagement time obtained from the video records:

Table 3: Descriptions of students' engagement time

		Engagement Time (minutes)			
		Minimum	Maximum	Mean	Std. deviation
Learning Modules	Phase Change (N=13)	17	82	44.08	19.35
	Heat (N=17)	23	83	51.18	16.35
Prior Online Experience	Yes (N=20)	20	74	46.90	15.96
	No (N=10)	17	83	50.50	21.64

Table 3 indicates that the mean engagement time (*M*= 46.90, *SD*= 15.96) of the experienced group was lower than the inexperienced cohort (*M*=50.50, *SD*= 21.64). Nonetheless, the engagement times of the inexperienced group are more spread out compare to experienced group. Also, the inexperienced group took longer in their initial time spent in becoming familiar with the online environment. As found from the observation and video record data, inexperienced students generally engaged for an extended period (varied between 2 to 5 minutes) at the start of the module in orienting or understanding the simulation environment. This prolonged initial familiarisation with the environment resulted in less engagement time attributable to exploring the target concepts. For example, one student exhibited a difficult time initially with a simulation activity that was intended to provide the student with an opportunity to learn basic ideas relating to the *states of matter*, i.e., the solid, liquid and gaseous phases of a substance (see *figure 5*). During interview, this student explained the reason for their initial difficulty:

I think I am trying to move it (the lid of the container) up. Whenever I moved it up, I saw the cursor goes away, oh! and I lost it. Also, it took me a little while to realize how the pump works (in the simulation model). [p207]

This confirms that the student had faced initial difficulties in understanding the functions of the simulation parameters (e.g., use of the container lid to change the pressure, and the pump to increase the volume of the substance). Another interview example reveals a different student's reasons for their initial difficulty.

It took me a bit of time to figure out how to work with the play (button) and then pressing the heat (button) up for a long time to get the temperature up. [p103]

This observation suggests that inexperienced students had trouble initially with navigating the simulations and therefore they took longer to engage with the activity than the experienced group.

Independent sampled *t*-test suggests that there were no significant differences between the mean engagement time of the experienced and inexperienced student groups $t\ (28) = .486$, $p > .05$. It was found, *table 4,* that both groups satisfied the condition of homogeneity of equal variances (F=.498, p=.486).

Table 4: Significance test between the mean engagement time of the student groups

	Levene's test for equality of variances		t-test for equality of means		
	F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**
Equal variances assumed	.498	.486	.517	28	.609
Equal variances not assumed			.466	14.068	.648

Student engagement time with separate individual activities across the learning modules was explored further, a *chi-square* test of independence was conducted to ascertain if there was any significant association between engagement time and the types of activities.

Table 5: Students' engagement time with individual activities

Activities	Engagement time counts		Chi square result	Post hoc analysis	
	Low	*High*		*Adjusted Residual*	*Adjusted P-value*
Text and Images	14 (46.7%)	16 (53.3%)	χ^2 (4) = 27.551	-1.54	0.618
Open Response	20 (66.7%)	10 (33.3%)	Sig. (2-sided) = 0.000; p < .05	-4.12	**0.000**
Feedback	4 (13.3%)	26 (86.7%)	Cramer's V = 0.43	2.75	**0.030**
Videos	4 (13.3%)	26 (86.7%)	N = 150	2.75	**0.030**
Simulations	10 (33.3%)	20 (66.7%)		0.17	4.325

The *chi-square* test of independence, in *table 5*, revealed a significant association between engagement time and the types of activities, *chi-square (*4, N = 150) = 27.551; $p < .05$. Post hoc analysis revealed that among the types of activities, engagement time in open response, feedback and in videos are significantly differ from the expected count of the null hypothesis. This indicates that videos and feedback attracted significantly higher engagement time, and open response entries resulted in significant low engagement time.

It should be noted that the simulations were presented as the central activities in each of the learning modules so it was hypothesised that they would attract longer engagement time, but the data suggests otherwise. During the interview, students expressed why they had preferred videos and had engaged for longer period of time with this mode compared to simulations.

I love the videos because it does not require so much input on your part. You can just sit back and take it all visually. [h102]

I prefer video to the simulation because it explains the things in a very short way. [h204]

I think naturally anyone is happy to see the videos. It explained well, and it helped my understanding about the structures of the water molecules in different phases. [p206]

The data suggests that the videos were easier to understand and did not require any physical interaction from the students, i.e., no active interaction with the content was required. Students appeared happy, and probably intrinsically motivated to engage with the videos as they could act receptively during the activities.

The interviews with students also revealed that they had spent time in engaging with feedback because they were intrinsically motivated to know whether their answer was correct or incorrect.

I like feedback. I think it makes understanding clear. [p207]

It was good to have that feedback and the little video afterwards. Now I know why I got it wrong and I will not get it wrong again. [h101]

If I did not get the feedback and if I did not know the answer, I would just carry on without really understanding the concept. But because it gives you the opportunity to answer and then give feedback on it, yeah, I think that is really helpful. [p103]

The above comments support the effectiveness of the feedback mechanism as scaffolding to engage students more deeply in activities, an outcome similar to that noted in a previous study (Mount et al., 2009).

5.2 Student effort applied to the task in different instructional settings

Persistence and systematic investigation were examined to identify students' behavioural effort during the S-C interaction process in three different instructional settings.

Table 6: Students' persistence in different instructional settings

Instructional Settings	Persistence		Chi-square result	Post hoc analysis	
	Low	*High*		*Adjusted Residual*	*Adjusted P-value*
Minimal or Open Ended	19 (79.2%)	5 (20.8%)	χ^2 (2) = 15.579 Sig. (2-sided) = 0.000; p < .05	-3.92	**0.000**
Moderate	6 (26.1%)	17 (73.9%)	Cramer's V = 0.48	2.48	**0.039**
Strong	7 (33.3%)	14 (66.7%)		1.52	0.386
	Systematic Investigation				
	One concept and below	*Two concepts and above*			
Minimal or Open Ended	18 (75.0%)	6 (25.0%)	χ^2 (2) = 5.608 Sig. (2-sided) = 0.061; p > .05 N = 68		
Moderate	11 (47.8%)	12 (52.2%)			
Strong	9 (42.9%)	12 (57.1%)			

In table 6, the *chi-square* result shows a statistically significant association between instructional settings and student persistence, *chi-square* (2, N = 68) = 15.579, $p < .05$. Post hoc analysis did confirm that students show significant high persistence in moderately guided activities and significantly low persistence in the minimal or open-ended instructional settings. Similarly, students showed a tendency to demonstrate more systematic investigation in the guided activities compared to unguided activities. However, the *chi-square* test shows that the association between instructional settings and students' systematic investigation were not statistically significant, *chi-square* (2, N = 68) = 5.608, $p > .05$. So, students' systematic investigation was not directly influenced by the instructional guidance.

In brief, activities without the instructional guidance were perceived to be less effective by students. The original intention of open and minimally guided activities was to support students' independent exploration and learning. It was found from observation of behaviour in this study that this strategy did not work well for students, this finding is further supported by the data from the student interviews shown below:

It is not clear about the objective of this simulation. There should be clear instructions of the activities in the simulation (activity). [h206]

There are some parts (in simulation), need to do some activities but there are not enough instructions for me. So, I am struggling there. [h204]

The simulation was pretty hard to understand. Because I had to play around the things myself. It will be better if there was somebody voicing over or explaining it to me. [p205]

Additional specific insights into why open exploration of simulations might have hindered students are provided in the more extended example of a student's open exploration process below.

The simulation activity considered here was taken from the *Heat* topic module in which minimal guidance was strategically and deliberately offered. It represents the concept of thermal expansion at the molecular level (*figure 6*). The simulation has two important interactive tabs (functions) labelled 'Heat' and 'Cool' that enable the student to change the heat in the system. A student can initiate their independent exploration by clicking on either of these tabs.

One student [H103], during the interaction, was observed to continually attempt to increase the system heat by clicking on the '*Heat'* tab, disregarding the *'Cool' tab* which could have been used to reduce the system heat for comparison. In the interview, the student explained their behaviour:

"I just heated it all the way to see how to get it overflow (with the system heat). Because that was my intention. I did not think to cool down the system heat" [h103].

Students demonstrated that their exploration of the simulation model was found to be both beneficial and unproductive. For example, the above student sought to find out what might happen to an object when extreme heat was applied. Intuitively, freedom in general to explore a simulation, seems appealing. Consequently, this autonomy in learning led them to have a new experience with the simulation model, perhaps, supporting the construction of new knowledge about molecular behaviour. In contrast, such freedom in the exploration might be interpreted as reaping unproductive results. In particular, overlooking the 'Cool' tab deprived the student of experiencing the molecular behaviour at a low temperature, and consequently probably left them in a state of incomplete understanding of the thermal expansion process; that is, it was observed that the student had missed the opportunity to experience the effect of a low temperature on the behaviour of molecules.

This study also found that, despite the known benefits of guided activities, some students preferred the open nature of the activity. There was evidence of belief that the simulation and its affordances were enough to support their self-exploration. A student in this category clarified their view in the post-module interview:

I think simulation itself can guide. The whole idea is kind of like make your own way through … and play around with all the concepts. Manipulate all these things and answer the questions, do what you want… you can do the most things you really like, kind of get yourself involved and learn in deep level sometimes. [p207]

The ability to '*do what you want*' was captivating for this type of student who appeared keen to embark on the self-exploration. This infers that the implicit guidance instigated from the learning environment coupled with the consequences of the exploration met their requirements adequately.

5.3 The influence of prior online experience

The dichotomy in experience with exploring a simulation such as the one described above was investigated further in terms of whether the association between instructional settings and student persistence was influenced by prior online experience. Prior online experience was added as a control variable in the statistical analysis to ascertain its effect on students' level of persistence and systematic investigation in different instructional settings. *Fisher's Exact* test seems appropriate here, as expected frequency is lower than 5 counts in the contingency table for *chi-square* test. Therefore, a 2x2 contingency table has been formed by combining the moderate and strong guidance under 'guided' category and open/minimal guidance has put under 'unguided' category.

Table 7: The influence of Prior Online Experience in students' persistence

Prior online experience	Behavioural effort	Instructional Settings		Fisher's Exact test of independence
		Unguided	*Guided*	
No	*Low persistence*	6 (66.7%)	6 (37.5%)	Exact Sig. (2-sided) = .226; p > .05
	High persistence	3 (33.3%)	10 (62.5%)	
Yes	*Low persistence*	13 (86.7%)	7 (25.0%)	Exact Sig. (2-sided) = **0.000; p < .05**
	High persistence	2 (13.3%)	21 (75.0%)	Phi = 0.589
No	*One concept and below*	6 (66.7%)	9 (56.3%)	Exact Sig. (2-sided) = 0.691; p > .05
	Two concepts and above	3 (33.3%)	7 (43.8%)	
Yes	*One concept and below*	12 (80.0%)	11 (39.3%)	Exact Sig. (2-sided) = **0.023; p < .05**
	Two concepts and above	3 (20.0%)	17 (60.7%)	Phi = 0.389

Table 7 indicates that *Fisher Exact* test for the experienced student group showed statistically significant association between instructional settings and student persistence (Exact Sig. 2-sided) = 0.000; p < .05; and between instructional settings systematic investigation (Exact Sig. 2-sided) = 0.023; p < .05. The strength of the associations measured in *Phi value* showed strong association (0.589 and 0.389) for both the persistence and systematic investigation for the experienced group. In contrast, for the inexperienced student group, the *Fisher Exact* test shows that instructional settings do not significantly associated with persistence and systematic investigation. This result indicated that the experienced students are more capable of utilising the instructional guidance to engage meaningfully with the learning content in the self-directed environment. Overall, guided activities tended (as the % value indicates) to support higher student persistence and systematic investigation than activities that provided minimal support for the students.

5.4 Students' task completion rate

Based on the number of S-C interactions, the student task completion rate was found to be higher for videos (93.6%) compared to simulations (55.9%) and open response questions (51.3%), as illustrated in the *table 8*.

Table 8: Frequency of task completion in different activities

Activities	Total interactions (N)	Completion frequency	Completion rate (in %)	Nature of participation (Source: Observation)
Open responses	236	121	51.3	Required written input and cognitive effort to process learning
Simulations	68	38	55.9	Required manipulative and cognitive effort to process learning
Videos	47	44	93.6	Required cognitive effort to dual process information in learning

Table 8 shows that the students exhibited reluctance to respond to open-ended questions with a response rate of 51.3% (around half) for the inquiry questions asked in the learning modules. Interview data indicated that for several students, an incomplete response could be attributed to their understanding still developing hence their inability to explain the concept.

I was tweaking in my mind (about the ideas) and sometimes it took longer time to do the things. Obviously, the concepts were not concrete in my mind and so obviously the understanding. [h102].

I guess that I kind of knew the concept, but I did not really know how to word them. I had some sort of idea in my head but actually articulating them scientifically was what I had difficulty with' [h205]

This suggested that students struggled in interpreting and reformulating their thoughts and ideas into precise explanations and therefore left these answers incomplete.

The findings in *table 8,* also supported by the interview data, further confirm those observed in *sections 5.1* and *5.2,* where students generally revealed a positive attitude towards the video activities (completion rate 93.6%). Altogether, these data suggest that the video format attracted higher student engagement, albeit receptively. The simpler and less technically difficult videos demanded lower manipulative effort which in turn enabled students to participate visually and, perhaps, were supportive of their receptive understanding of the concepts (blinded). As simulation activities are the central component of the learning modules, further exploration of students' task completion rate in simulation activities in the three different instructional settings was considered.

Table 9: Students' task completion rate in simulation activities in various instructional settings

Instructional guidance	Task Completion		Chi square test of Independence	Post Hoc Analysis	
	No	*Yes*		*Adjusted Residual*	*Adjusted P-value*
Minimal or open-ended	17 (70.8%)	7 (29.2%)	χ^2 (2) = 11.274 Sig. (2-sided) = 0.004; p < .05	-3.28	**.003**
Moderate guidance	8 (34.8%)	15 (65.2%)	Cramer' V = 0.407 N = 68	1.11	.801
Strong Guidance	5 (23.8%)	16 (76.2%)		2.25	.073

The *chi-square* test of independence in *table 9* reveals a statistically significant association between instructional settings and students' task accomplishment, *chi-square* (2, N = 68) = 11.274, *p* < .05. The post hoc analysis confirmed that it is the open-ended/minimal guided activity that causes the statistically significantly low task accomplishment rate. In contrast, the analysis clearly suggests that the guided activities provided support and motivation to students to complete the tasks. This finding supported the previous findings discussed in detail in *section 5.2* that the students' degree of effort was lower in open-ended exploratory tasks. Further, students prior online experience was added as a control variable and *Fisher Exact* test has been conducted to understand how prior online experience impacted students' task accomplishment rate.

Table 10: Influence of prior online experience on task accomplishment

Prior Online Experience	Instructional Settings	Task Completion		Fisher's Exact test of Independence
		No	*Yes*	
No	*Unguided*	5 (55.6%)	4 (44.4%)	Exact Sig. (2-sided) = 1.000
	Guided	8 (50.0%)	8 (50.0%)	
Yes	*Unguided*	12 (80.0%)	3 (20.0%)	Exact Sig. (2-sided) = **0.000; p < .05** Phi = 0.606
	Guided	5 (17.9%)	23 (82.1%)	

In *Table 10 FisherExact* test reports a statistically significant association, (sig. 2-sided) = 0.000; p < .05 between the instructional settings and higher task completion rate for the experienced student group. This indicates again that experienced students can best utilise the instructional settings in a self-directed environment.

6. Discussion

Several factors that affect student behavioural engagement focusing upon S-C interactions have been explored in this study in the context of an online learning environment. Based on the behavioural constructs reported in the literature (such as time on task and quality time spent) and the factors derived from the online context related to student and content, a relationship model is proposed.

In this model, student behavioural engagement was conceptualised based on the relationship between engagement constructs and engagement factors linked with the S-C interaction process. Engagement constructs were distilled from research literature while engagement factors were conceptualised from the data originating in the S-C interaction process. The underlying factors relating to both students and contents are illustrated in *figure 7*.

6.1 Factors affecting students' engagement time and task completion rate

Previous studies report that in an online learning context, students may lack motivation to engage with the content in the absence of teacher guidance (Fryer & Bovee, 2016). Nevertheless, the students' total engagement time in this study, with the two online learning modules was found to be satisfactory. This is likely due to the underlying POEE instructional design supporting students to regulate their learning in a series of inquiry phases (blinded). Also, as students worked independently without direct teacher support, a sense of being autonomous during the interaction might facilitate intrinsic motivation (Deci & Ryan, 1987). Therefore, the high engagement time achieved in this study supports the efficacy of the underlying pedagogical design of the learning modules. Previous studies evidenced that higher engagement time facilitated student performance in a variety of educational settings, such as in the traditional classroom context (Gromada & Shewbridge, 2016), in a blended learning environment (Raspopovic et al., 2014), and in online settings (Baragash & Al-Samarraie, 2018). So, the purpose of engaging students with the learning modules appears to have been fulfilled, supported by the underlying POEE pedagogical strategy.

The mean engagement time of the more experienced student group was lower than the student group who had no prior experience. This observation appears to contradict previous published results where experienced students tend to engage longer in utilising the available technology resources and therefore were able to engage more meaningfully in the learning processes (Bates & Khasawneh, 2007). In the current study, it was observed that inexperienced students spent more time initially investing in becoming familiar with the functions and orienting in the online environment. Experienced learners, in contrast, spent less time in familiarizing themselves with the environment and were observed to spend a greater amount of time engaged in actively processing understanding of the intended science concepts. It has been reported previously that when students utilise most of their cognitive ability on something that is extraneous, they often failed to engage meaningfully with the intended learning concepts with their remaining cognitive capacity (Mayer, 2019). This study provides further evidence that inexperienced students, due to their inappropriate use of cognitive capacity, demonstrated lower behavioural effort in persistence, task accomplishment, and they failed to utilise the incentives of instructional guidance provided in the self-directed environment. Future modification of instructional guidance should aim is to reduce the extraneous processing involved in the familiarisation with the environment by increasing the signalling and applying the contiguity principle (Mayer, 2017). One strategy that may be applied is provision of a brief narrated ‘tour’ of highlighted interactive functions with modelling of how to notice changes using simulations, further research is required to evaluate this form of intervention.

When considering individual forms of activity within the S-C interaction process, videos and feedback activities secured the highest time on task compared to the interactive simulations and open response activities. This aligns with a recent finding set in an open online course, undertaken by a large cohort, that a major proportion of the students (67%) focused almost exclusively on video lectures amongst all of the courses' components and activities (Kovanović et al., 2019). The findings in the current study similarly provided an explicit understanding that students were more engaged with video activities and self-reported that they did not need to engage in manipulative effort and active participation compared to the simulation activities and open responses where greater effort was perceived to be required. Thus, when students are engaged with video activities as part of the learning process, it might increase student satisfaction (Bhadani et al., 2017) and reap improved learning performance (Shen, 2014).

The greater task completion that was observed when videos were involved compared to the simulations and open response activities can be explained by the nature of interactions that are required, videos typically engage students receptively rather than interactively. Previous studies support the notion that a key reason that students are willing to dedicate their time to a task and persist to complete a task is the level of motivation that is aroused (Dev, 1997). In the online context, the psychological motivation factors accord with learners’ interests, motivation, and positive attitudes toward learning (J. Lee et al., 2019). According to Mayer’s dual processing theory, watching videos can contribute to the reduction of cognitive load due to the simultaneous use of auditory and visual channels (Mayer, 2005; Mayer, 2017).

In contrast to a video as a mode of content interaction, the simulation format requires manipulative interactions and demands active engagement with the activity. This ‘high element interactivity’ can cause working memory overload (Kehrwald & Bentley, 2020) thus inducing students to become psychologically demotivated in engagement to complete the task (J. Lee et al., 2019). This form of intrinsic load is inherent in the simulations because of its complexity. Research confirms increased complexity creates increased intrinsic load (Sweller, 1999). The current study did not offer any extrinsic motivation in the form of summative marks or certification hence the absence of external motivators might also contribute to the students’ low task accomplishment rate when a higher cognitive load is involved.

One strategy to reduce the extraneous cognitive load is to introduce explicit instructions to improve the value of the simulation, such as a narrated interactive video to orient students in the simulation functions (Mayer, 2017). This is supported by the temporal contiguity principle in which showing the graphical movement and background narration describing them simultaneously (Mayer, 2019). However, a balance needs to be achieved between the freedom to explore, which makes students cognitively active, and the guidance which is required to support cognitive activity to make meaningful construction of knowledge (Mayer, 2004). Mayer (2019) in his review of thirty years of research in online learning favours guided activities and passive media arguing that it can help students active cognitively during the learning process (Mayer, 2019).

Further findings in this study reveal that students sustained their engagement for a longer period of time due to the provision of immediate feedback following their response to concept questions. The feedback system employed, helped students to make a link between the discrete knowledge they had constructed of a concept towards a more comprehensive understanding. In fact, it was found that during interviews most students were in favour of receiving immediate feedback while studying online. Studies show that when students are motivated, they spent quality time in undertaking the online learning tasks (Romero & Barberà, 2011). Therefore, feedback can contribute significantly to motivating the students to ascertain whether their responses were right or wrong, adjust their understanding and continue. Therefore, student engagement time was rated as high in regard to the feedback activities.

In contrast, students were observed to engage less with activities that involved their submission of an open response explanation of a concept. This activity required students to cognitively process their understanding and translate them into words in entering a response. It was necessary for them to utilise their working memory in the process of synchronising both the manipulative and cognitive processes involved while writing their responses. This might create a high cognitive stress, through the imposition of a higher cognitive workload, eventually leading to a low engagement time with the open response activities and low task accomplishment. Apart from the demand for physical input, there were a few other factors that militated against students completing their answers, for example, shallow understanding of the concepts and their cognitive inability to respond to the questions correctly. Research shows that cognitive ability is an important element in the completion of a learning task (Sweller, 1988; Sweller et al., 1998). As the findings of this study revealed, students were presumed to know the associated science facts but failed to respond with adequate explanations; as a result, they most frequently left the answer incomplete. Therefore, there is a need for module designers to tailor the open response activities by providing ‘hints’ to facilitate students’ thinking in translating their ideas into explanations that are scientifically correct.

6.2 Student persistence and systematic investigation in the guided activities

The other important factors affecting students’ quality time are persistence and systematic investigation. Students were more likely to demonstrate high persistence and systematic investigation in guided activities than they were in minimally guided or open-ended instructional settings. Previous studies support this notion that guided activities attract higher student engagement (Fisher, 2010; Mason, 2011). Significantly, a recent study in inquiry-based STEM education confirmed that the higher the provision of guidance in an online environment, the higher the commitment students demonstrated in engaging with an activity (Sergis et al., 2019).

This study, to some extent, found that open exploration often reaps some positive results in the long run, as illustrated in the example described in *section 5.2*. In such a study space, being an independent learner means such a student is intrinsically motivated to explore a simulation (Deci & Ryan, 1987). Students might find such an open exploration appealing to them as they are afforded the opportunity to have a satisfying experiential learning experience. When such an open environment is created, many students engage in some productive exploration (Podolefsky et al., 2009).

Nonetheless, in the open exploration context, students were often unsuccessful in learning the underlying science concepts. In the example provided in *section 5.2*, the student only raised the heat to observe a change, they could have lowered the temperature to zero to experience how molecules stopped vibrating and completely froze, an opportunity that is impossible to view in the real world. So herein resides a pedagogical conundrum. Open exploration can lead students to acquire new information and construct new knowledge; yet they may not achieve the intended learning if they miss an opportunity. In offering a degree of latitude, it is possible that only partial success will be realized. In fact, most of the previous studies reveal that inquiry learning without guidance is less successful (Alfieri et al., 2011; Clark et al., 2012; Kirschner et al., 2006; Lazonder, 2014; Luo, 2015). Additionally, open exploration in a technology rich environment can create a high cognitive load which can disadvantage the learner (Paas et al., 2003; Sweller, 1999). Moreover, students are often led to incorrect conclusions when they are left on their own to explore and use the technology resources (Podolefsky et al., 2009). Therefore, a guided scaffolded design might be necessary to support students effective learning in the inquiry-based learning environment.

6.3 Prior experience to influence student persistence and systematic investigation

The findings revealed that prior online experience significantly improved students' level of persistence and systematic investigation in the guided instructional settings. Students' behaviour of demonstrating high persistence and systematic investigation support the idea that in the guided environment experienced students can better utilise the educational resources compared to their non-experienced peers. Studies also show that experienced students are more successful in their use of technology-mediated inquiry-based learning environment (H. S. Lee et al., 2010; Pallant & Tinker, 2004). Moos and Azevedo (2008) further added that experienced students can engage with exploration meaningfully through more discriminating selection of new resources from the technology mediated environment. Therefore, it is unsurprising that experienced students demonstrate higher self-efficacy in the technology rich environment (Cheng & Tsai, 2011) and commit to spending more time with the learning contents (Bates & Khasawneh, 2007).

In contrast, Meyer (2014) argued that inexperienced learners were prone to a lack of engagement due to insufficient skills in this environment. In the technology environment, inexperienced students' cognitive capacity become depleted as they have already utilised a significant portion of their working memory in getting to know and explore the rich contents prevalent in this environment (Kehrwald & Bentley, 2020).

7. Limitations And Further Research Implications

The conceptual and empirical work cited above did not consider the multiple dimensions of student engagement; rather it focused only on students' behavioural aspects. Studies show that there are situations when a student can demonstrate high cognitive engagement yet are committed affectively and behaviourally at lower levels. Similarly, a student can find a task to be important for learning, yet not capitalise on this understanding during interaction because the activity itself might not be personally enjoyable and interesting (Schmidt et al., 2018). Also, a student can demonstrate strong behavioural engagement, but invest less cognitive and affective effort, inferring that the student completed the task but very likely did not learn much from the exercise. Studies also show that students with low cognitive engagement usually struggle in understanding the concept and therefore adopt a surface level approach, focusing on completing the task as a means to end the activity instead of striving to understand the concept at a deep level (Fredricks et al., 2004). So, many scenarios are possible, but this study did not consider the multidimensional engagement context to allowing for a coordinated result about student engagement and learning.

This study used the POEE design framework to encourage students to become independent learners in an inquiry-based self-directed learning environment. As revealed, the absence of any guidance potentially secured less productive learning for some students. Nevertheless, strong guidance does not necessarily ensure the best learning experience either. A possible disadvantage of strongly guided support is that it might limit a student's autonomy in the learning process and reduce the chance of their becoming independent learners, a phenomenon which was explored in this study. This dilemma of the balance between no guidance versus over-guidance needs to be explored further so future studies might experiment with various pedagogical designs to address this issue.

Another potential direction for future studies resides in the use of the POEE design to employ gradual reduction of the degree of guidance from the learning activities to encourage students towards adopting more responsibility in the process of becoming independent learners. This design could provide novice learners greater continuity in learning and lead them to develop coping mechanisms for interacting more productively with more complex online learning environments (Arbaugh, 2014). Research shows that when students experience similar activities repeatedly, they become more familiar with the technology resources and achieve a certain degree of control over the environment, therefore, becoming more independent of instructional guidance (Li et al., 2019).

Finally, this study involves the application of design principles with a small sample of undergraduate participants in a single context hence the findings contribute to increasing the collective body of research evidence that combines to inform practice rather than being claimed as generalisable outcomes. Mayer (2017) proposes a research agenda that supports inclusion of studies that explore the application of design principles to advance understanding of student engagement, behaviour and learning outcomes using multimedia.

8. Conclusion

The underlying POEE scaffolding strategy implemented in the multimedia learning modules highlights the student-content interaction process within the paradigm of individual cognitive constructivism. As no teacher or peer support was included in this study context, the findings of this study revealed several salient factors implicated in understanding the student content interaction process in the self-directed inquiry-based learning context. These factors are conceptualised to explain student behavioural engagement in this novel context that can support educators in creating learning environments conducive to supporting students in becoming independent learners. The relationship between the engagement constructs and engagement factors can further support educators in designing their instructional strategies applicable to an effective self-directed learning environment.

9. Declarations

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Conflicts of interest

The authors declare that they have no conflict of interest.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

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Figures

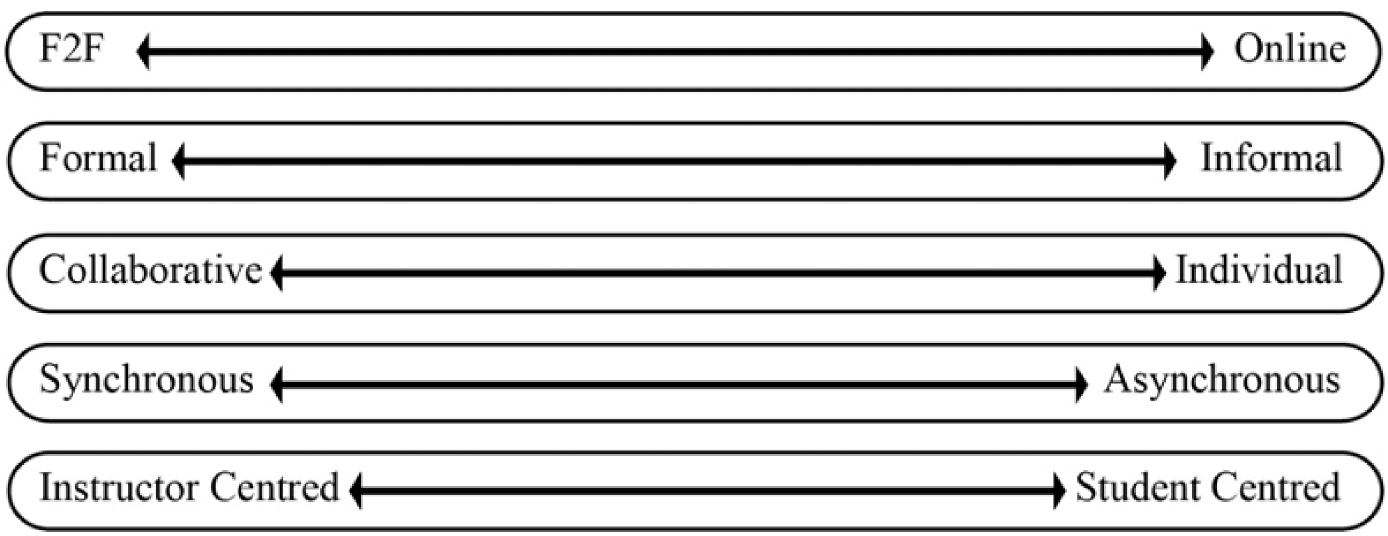

Figure 1

Variable conditions and participants in online learning environments (F2F: face-to-face)

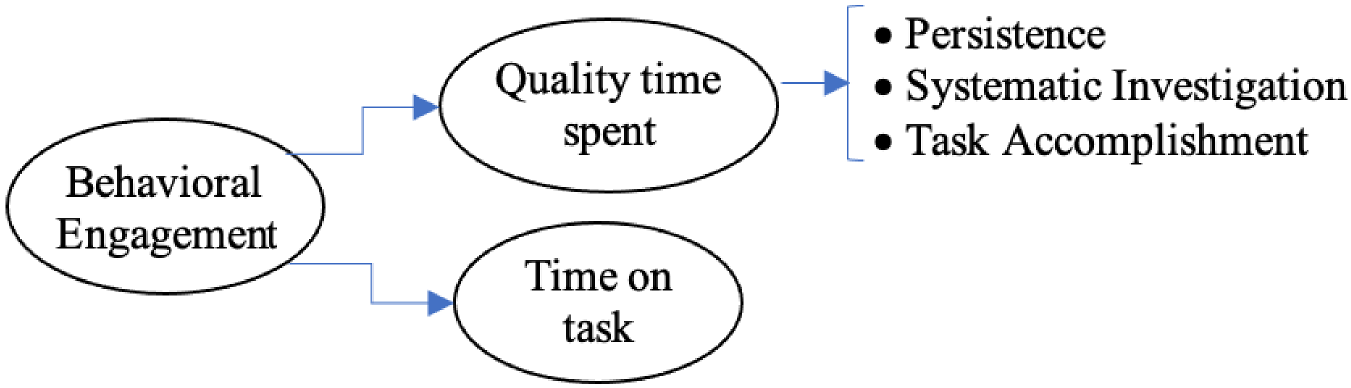

Figure 2

Conceptualisation of student behavioural engagement in online environment

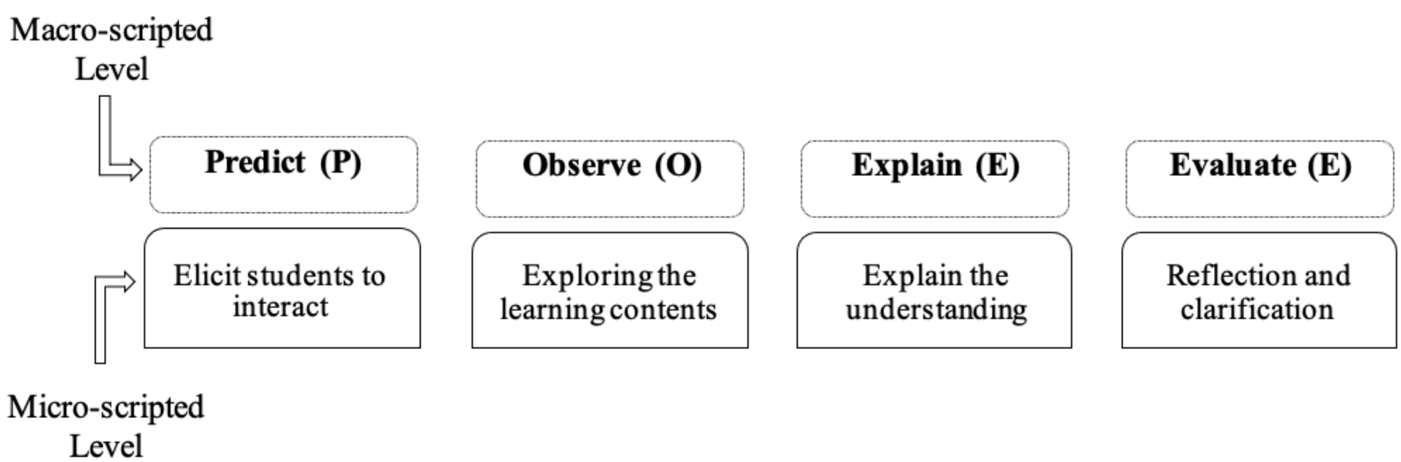

Figure 3

POEE scaffolding framework to design two online learning modules (bilinded)

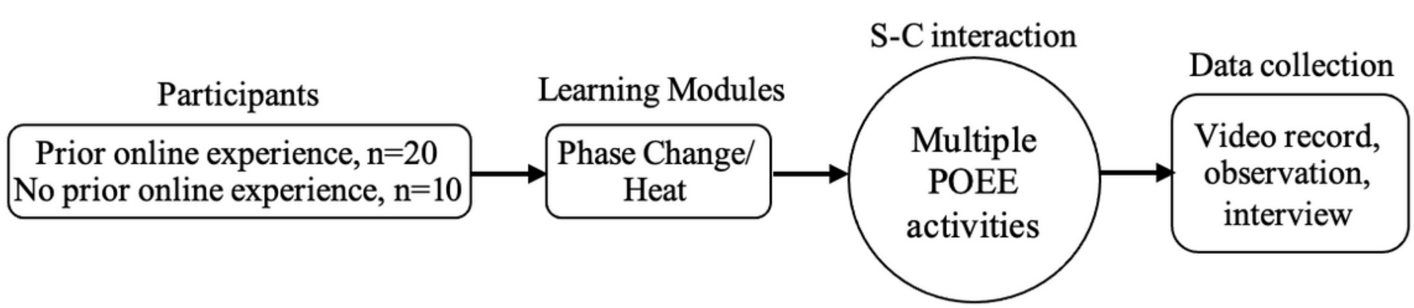

Figure 4

An overview of the study environment

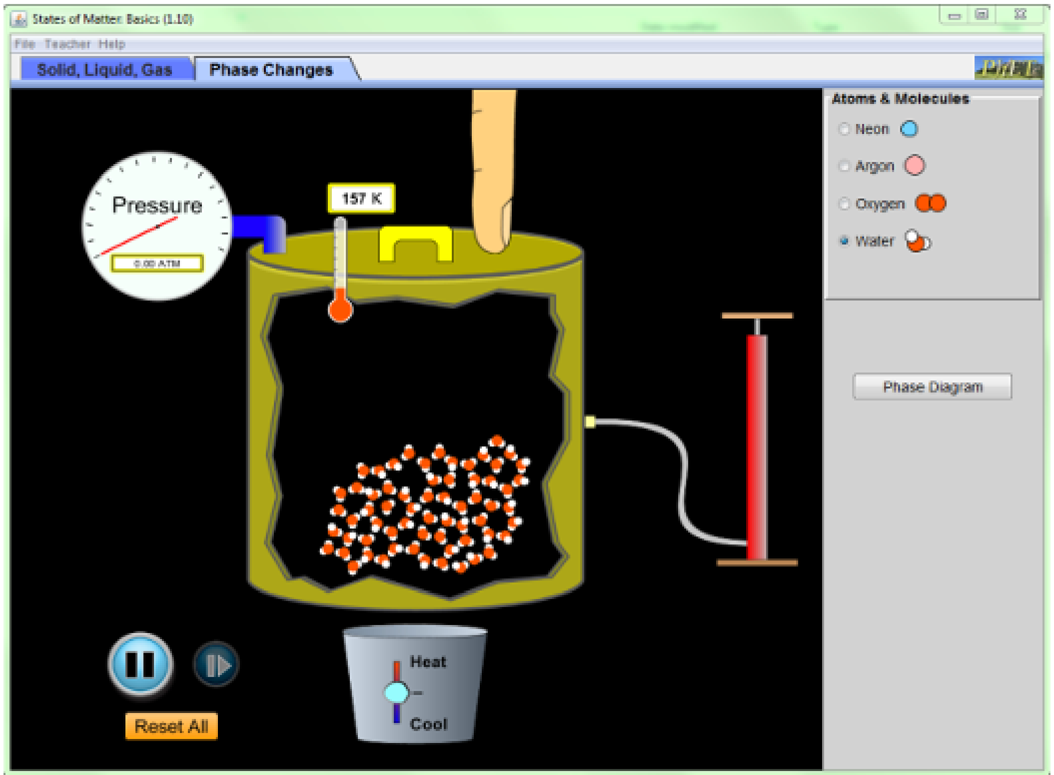

Figure 5

‘States of matter: Basics’ simulation model (PhET, n.d.)

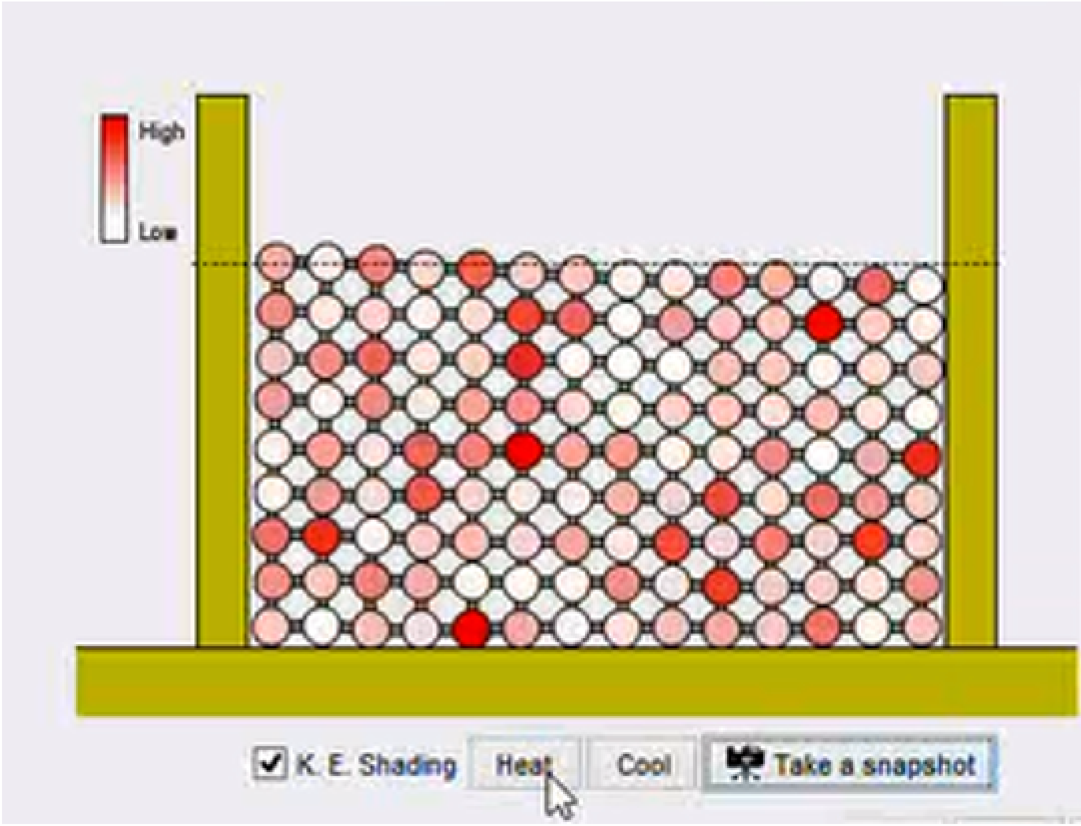

Figure 6

Thermal expansion simulation model from Heat learning module (MolecularWorkbench, n.d.)

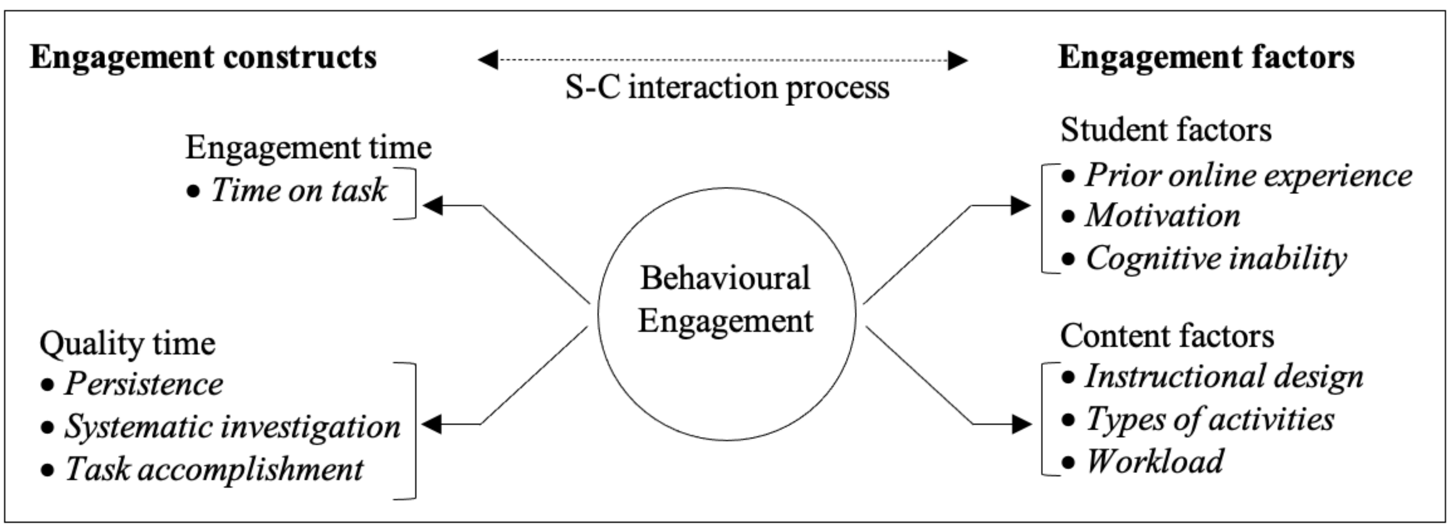

Figure 7

Conceptualisation of behavioural engagement for student-content interaction processes