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Understanding optimal problem-solving in a digital game: The interplay of learner attributes and learning behavior

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ABSTRACT

Educational video games, with various motivational features and scaffolding support, have high potential for facilitating optimal learning and achievement. However, research on how students utilize game features, identify useful information, and explore solutions to in-game problem scenarios continues to be under-researched. This study aims to unpack the mechanisms underlying users' in-game behaviors to identify emergent markers of optimal problem-solving performance in an educational video game. Survey data and computer logs were collected from 61 participants (36.4% middle and high-school students, $M_{age} = 13$; 63.6% university students, $M_{age} = 21$) to address the research inquiry of the present study. Results from the regression analysis not only showed an important link between individual characteristics (i.e., self-efficacy, prior knowledge) and success-striving in-game behavior, but also highlighted the role of self-regulated help-seeking behavior in determining students' optimal problem-solving pathways. Our findings add new perspectives to existing research of what learning behaviors are crucial for promoting self-regulation in digital game-based learning. These findings provide useful insight on how to design scaffolding tools in an open-ended problem-solving space to encourage student engagement in effective help-seeking behaviors for optimal learning performance.

1. Introduction

Optimizing learning behavior and performance is the goal of effective instruction and learning, which has been an interest of educators and researchers alike for many years. Optimal learning is defined as a learner using a high level of skill to meet a significant challenge while sustaining elevated concentration and interest in learning [1–4]. It is governed by three interactive factors: *personal* (e.g., learner attitudes and expectations), *behavioral* (e.g., the ability to invoke relevant prior knowledge and to employ appropriate strategies to support learning) and *environmental* (e.g., instruction support and feedback). Studies on game-based learning have indicated that educational video games have high potential for facilitating optimal learning experience and achievement [5,6]. Educational video games provide self-directed and open-ended learning spaces where multiple representations are integrated to present complex information and problem solving is a pervasive activity [7]. As such, the exploration of information and finding solutions to problem scenarios in video games is often a non-linear process that requires a high degree of learner control and persistent effort. Problem solving is the process of problem analysis and finding an appropriate solution that can best resolve the issue. During gameplay, problems may occur when an individual lacks a clear path towards achieving the goal and has difficulty finding potential solutions [8]. To appropriately engage in problem-solving, individuals must first recognize a problematic situation, understand the nature of the situation, and then identify, plan, and carry out potential solutions. Increasing research has shown that success in problem solving is highly determined by students' overall disposition, such as motivation [9], goal value [10], emotion [11], self-regulatory knowledge [12], and their level of expert knowledge [13]. For instance, students who demonstrate self-regulatory behaviors in problem-solving tend to make better use of in-game resources and are more deliberate in their actions to search for appropriate resources to help them solve problems, resulting in higher learning gains [12].

Although, educational video games are reported to have high potential for enhancing engagement [14] and promoting problem solving skill development [5], research on how students navigate and utilize game features, as well as leverage information to improve task performance continues to be under-researched [15,16]. In a video game, the user-system interactions often reflect a complex relationship among

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individual attributes, performance, and the challenges of quests afforded by the game [17,18]. To understand how students identify useful information and explore solutions to solve problem scenarios in video games, researchers need to capture a variety of in-game behaviors, identify meaningful patterns in behavioural responses, and more importantly, understand the interplay of students' individual differences, behavioural responses, and in-game task characteristics. Therefore, the current study aims to unpack the psychological mechanisms underlying students' in-game behaviors and identify emergent markers of optimal problem-solving performance in a video game. With this mind, the current study used both survey data and computer log trace data to uncover students' individual learning characteristics and how they relate to optimal problem-solving performance in the game environment. Computer log trace data provides a wealth of information about learner behaviors that can be captured and monitored for the purposes of detecting learning trajectories and patterns of interest [19]. The use of self-reported surveys and temporal log data provides us with a significant source of information about students' learning processes and their engagement with the learning environment. Linking both self-reported and behavioral indicators of student optimal problem-solving performance in educational video game environments can help us better identify the difference between expert and novice problem-solvers and, more importantly, we can use this information to design effective intervention to assist students to achieve optimal learning. The remainder of the paper starts with a section that presents the conceptual elements of optimal learning with digital educational video games. Section 3 describes the objectives and research questions which guide the construction of this study. In Section 4, we describe the research setting, sample population and the data sources. Further, in Sections 5 and 6, we present the findings and discuss the results in light of the research questions and literature review. Finally, Section 6 contains the relevant conclusions and contributions of the study. We conclude with limitations and ideas for future research.

2. Theoretical framework

2.1. Game-based learning and optimal engagement experience

Game-based learning (GBL or video games for learning purposes) uses games as vehicles to support learning of various competencies. Over the past 15 years, there has been an influx of game-based learning environments to help students learn specific educational material by using video gameplay (author, 2017; [20]). Gameplay creates a learning culture that incorporates a specific interest students have, adaptive challenge, and ongoing feedback to sustain optimal engagement and learning [21].

Video games have various motivational features that can sustain interest and cultivate optimal engagement, such as clear goals, challenge-skill balance, rewards, and agency [22,23]. These features are typically coupled with scaffolding tools to enhance students' motivation and learning [6,24]. For instance, studies have reported that the challenge-skill dynamic drives engagement and persistence in learning activities [2,24]. As game researchers have claimed, the challenge-level of a learning task always lies at the outer edge of a player's ability, and the difficulty level of the learning task increases when a player is repeatedly exposed to the game environment [22,25]. The continuing cycle of new challenges requires persistent attention and effort from the player, leading to a higher level of competency targeted by the game. In addition to the challenge-skill dynamic, game features, like clear goals and agency, are key factors to optimal engagement during gameplay and learning [5]. Agency, according to the game design literature, refers to the degree of freedom and control afforded to a player to perform actionable behaviors (for a review, see [26,27]). In a video game, players have the freedom to explore and interact with game elements based on their own goals, whilst selecting and organizing appropriate resources to help them solve problem scenarios. Players also have the freedom to control the gaming process and difficulty levels of the game [14]. Both freedom and control can increase player's perceived autonomy, which is intrinsically motivating and can be treated as a critical metacognitive component for self-regulated learning [28]. Findings from a systematic review of self-regulation in GBL environments suggested that students who felt in control of their motivation, learning goals, and progress, showed more learning gains and performed better in user-controlled settings [25]. Thus, in accordance with the aforementioned factors of optimal learning in traditional education settings, motivational game features, such as an optimally challenging task, a clear focus on goals paired with high task importance and expectations, user control, and the use of appropriate tools/strategies for problem solving can be considered as the primary characteristics of deep engagement and optimal performance within GBL environments. Deep engagement is a psychological state experienced during an activity that has both cognitive and behavioral components [29]. Researcher have discovered that successful in-game behaviors are developed by allowing players to experience immersive cognitive engagement [30,31]. For example, well-designed video games provide various problem-solving scenarios that mimic real-world problems and are highly authentic and personal to students [23,32], which not only trigger interest and sustain motivation, but more importantly, allow students to practice a wide array of problem-solving techniques with zero consequences, in turn supporting competency development and further knowledge acquisition [21]. As such, by implementing game-based learning that is engaging, authentic, and prompts the use of effective learning strategies, students' optimal problem-solving performance are likely to follow.

2.2. Self-regulated help-seeking in game-based learning

Self-Regulated Learning (SRL) is a self-directed method through which an individual uses cognitive, metacognitive, and affective processes to monitor their understanding [33,34]. Most often, self-regulated learning takes place in learning environments, such as classrooms, and requires learners to plan, monitor, enlist cognitive control, and react and reflect [33,35]. To meet their goals, students can enlist any of these strategies. In digital game-based learning environments, different components are used to promote engagement and motivation [23,36], as well as promoting the use of SRL strategies [37]. In particular, help-seeking, a goal-directed and intentional action, is considered an important self-regulated learning strategy [38–40]. It involves a person identifying problems, recognizing a need for help, and actively soliciting help to acquire knowledge to accomplish a task [41]. Seeking help requires both cognitive and social competencies, as well as personal and contextual motivational resources [39,41,42]. To seek help effectively, a student needs to know when the help is necessary and who is the best person to ask for help. The student also needs to evaluate whether the help received is relevant to the task being performed and whether help-seeking behavior is facilitated and supported in the learning context. Empirical evidence has indicated that students, who seek active control of their learning tend to ask for help more often [41]. Help-seeking mediates the relationship between academic difficulty and successful task completion [43]. Correlational findings of help-seeking research have shown that students' help-seeking preferences are linked with student achievement levels [44]. For example, in Reeves and Sperling's [44] study on student preference for help-seeking sources, the researchers found that high achieving students are more strategic in their help-seeking and are better able to determine the best method of interacting with the instructor as compared to their lower achieving peers.

In recent years, there has been an increased number of educational technologies developed to support students' learning, and as a result, students have more ways of interacting with various help modalities to improve their learning gains [45,46]. For example, intelligent tutoring systems provide users with different levels of help, ranging from hints, interactive glossaries, hyperlinked text, to scaffolds [45,47]. In educational video games, users can engage by clicking around the page, searching for clues, and asking virtual characters for explicit instructions. The most frequently used support features in digital GBL environments are hints, learning prompts, glossaries, feedback, and explicit instruction [5]. Asking for a hint, according to Nelson-Le Gall's definition of help-seeking (1985), is considered as instrumental help seeking, which indicates that there is a desire for clarification or refinement of current knowledge. The use of in-game learning prompts can facilitate students' initiative to reflect upon the learning content. On the other hand, asking for a direct answer is treated as executive help seeking behavior because it signifies a lack of knowledge or a desire for task completion [48,49]. Such help-seeking normally places the responsibility on the helper so that it reduces the amount of time and effort required to complete the task [48]. Even though the findings of help-seeking research have shown that instrumental help seeking is positively related to academic motivation and achievement, whereas executive help seeking is negatively associated with motivation and achievement performance [50], what really matters is how students use the help. For example, frequent use of a help resource or quickly clicking through a help feature without thinking deeply about the implications of the help is often associated with poor learning [51]. These help-seeking behaviors are known as executive help-seeking. Nevertheless, the quality of students' help-seeking behavior can be improved if they apply self-regulated learning strategies in the process of seeking help. Students monitor the help search options, evaluate whether the help is suited to task requirements, and then seek help to solve problems. An overwhelming consensus among researchers has concluded that when students engage in self-regulated learning strategies in computer-based interactive learning environments, whether they are prompted or self-initiated, they have increased engagement and stronger understanding of learning material [12]. However, effective help-seeking actions lead to better learning and improvement for the student to transition to the next step towards goal attainment [51].

3. The current study

The aim of the current study was to identify key determinants of students' optimal problem-solving pathways in a narrative-centered intelligent video game, referred to as *Crystal Island. Crystal Island*, designed for 21st century learners, helps students to acquire competencies in both science and language arts through active participation in highly engaging problem-solving activities. To achieve our research goals, we first applied the operational indicators (extracted from computer log trace data) to assess the level of students' engagement in three in-game learning activities while working toward solving problems in *Crystal Island*. Second, we sought to identify the key behavioral determinants of student optimal performance in scientific problem-solving. The fundamental premise underlying this study is that students' motivation toward learning tasks influences how they approach and engage in learning activities. As such, students' multi-componential intrapersonal variables (e.g., prior knowledge, motivation, goal orientation, and strategy knowledge) were evaluated and their interactions with students' learning behaviors and achievement outcomes were also analyzed to identify the determinants of students' optimal problem-solving pathways in *Crystal Island*. It was hoped that the findings of this study could unpack the mechanisms underlying students' optimal learning in computer-mediated learning environments. The following research questions were proposed to address the inquiry goals of the current study:

Q1: What can be identified as highly engaging tasks when students interact with *Crystal Island* to solve scientific problems?

Q2: What in-game behaviors best predict successful performance in solving scientific problems with *Crystal Island*?

Q3: Is there a relationship between students' psychological traits and their in-game behaviors?

4. Methods

4.1. Participant

61 students were recruited in this study, which includes teenage students (ranging from grades 6 to 9) and university undergraduate students. Participants selected from these age ranges align with existing digital game literature [5,52] and empirical studies of game-based learning using *Crystal Island* (for a review, see [5,53,54,55]). Prior to the data collection, university's institutional review board approval was obtained and all participants were given clear information as to the objectives of the study, their role in it, and their right to consent and withdraw from the study at any time. The teenage student participants were recruited in southeast of Canada, where the residents' education level is higher-than-provincial average, and the household income is one of the highest in Canada (Canada Statistic Canada report, 2016). These participants were mostly Caucasians (85.7%), ranging from 11 to 16 years old (with a mean age of 13). 95.2% of participating students have previous experience playing video games, among which 38.1% of participants spend approximately 60 to 120 min playing video games weekly.

University student participants ($M_{\text{age}} = 21$) were recruited from a research-intensive university in Canada. Approximately 45.5% of the sample population was East Asians and 27.3% of the participants were Asian Indians. Caucasian students consisted of 9.1% of the participant population and 6.8% of the sample was Middle Eastern. The overall sample was ethnically diverse, which aligns with the population in that region. Further, the participating undergraduate students represented a variety of disciplines: life science (40.9%), social science (31.8%), statistics, (13.6%), and computer science/engineering (9.1%). Almost half of the participants (45.5%) were in their fourth year of undergraduate university study, and 75% of them took at least three science-related courses in the past two years. In terms of video game-play experience, 36.4% of the students spent approximately 60 to 120 min to play video games weekly. In addition, students who were older in age demonstrated a higher level of background knowledge in comparison to the younger participants. It was observed that sophomores had the highest baseline knowledge, followed by fourth-year undergraduate students and grade 10 students. On the contrary, sixth graders had the lowest level of baseline knowledge. Lastly, to address the research inquiry of the current study, participants were divided into two groups based on their achievement performance on solving problems within *Crystal Island*. That is, students who successfully solved the problems ($N = 23$) and students who failed to solve the problems within *Crystal Island* ($N = 38$).

4.2. Learning platform: Crystal Island

Crystal Island is a narrative-centered intelligent video game that integrates role play, scientific exploration, and complex problem solving. It was designed for microbiology and literacy education. The in-game activities emphasize the nature and practice of scientific inquiry. For over a decade, many researchers have included samples comprised of diverse age groups of learners (aged from 12y to 21y) and in various research contexts (e.g., classrooms, lab-based research settings), to investigate the impact of *Crystal Island*, a digital game-based learning environment, on learners' engagement and learning outcomes (for a review, see [53,54,56,55]). When a student begins *Crystal Island*, they play the role of a medical detective tasked with identifying the cause of an epidemic that has spread among a group of scientists on a remote island. The student must determine the disease transmission sources and recommend a treatment plan for the patients. The student explores the virtual environment from a first-person perspective by navigating between five buildings on the island, where the student can engage in a series of activities that involve collecting data, generating initial hypotheses, generating/differential provisional diagnosis, and forming conclusions via the use of gathered evidence. That is, the student will first generate hypotheses based on the clues that they gathered from conversing with virtual characters (i.e., four patients, a nurse, a lab technician, and two scientists), reading books/research articles, and viewing posters. The student will then run laboratory tests to test contaminated food items to identify the disease transmission sources. To successfully complete the game, a student also needs to complete a diagnostic worksheet and submit a correct treatment plan to the system. The diagnostic worksheet is used to record patient's symptoms, laboratory test results, the possible explanations for the disease transmission causes, and a final diagnostic decision can be made. In short, to solve the problems in *Crystal Island*, students are asked to tackle a series of problem-solving tasks (See Table 1 and Fig. 1).

4.3. Instrument

4.3.1. Motivation strategies for learning questionnaire (MSLQ)

In this study, the *Motivation Strategies for Learning Questionnaire* (MSLQ) was used to measure students' motivation and attitudes toward learning microbiology with *Crystal Island*, and the types of learning strategies they may have applied during problem-solving. The MSLQ is a widely used self-report instrument to measure students' motivation and self-regulated learning strategies at the course-specific level. According to Duncan and McKeachie [57], learners' motivation and learning strategies are not static traits, because motivation is dynamic and contextual-dependent, and learning strategies can be acquired and brought under the control of the student. In the motivation literature, there are two general approaches to understanding learner motivation and learning [58], namely, they are students' attitudes toward learning (SAL) and their style of engaging with learning tasks (i.e., self-regulated learning). According to Rotgans and Schmidt [58], SAL provides students' general learning orientations and study approaches, whereas self-regulated learning allows for insights into students' context-specific self-regulatory learning capabilities.

In this study, a total of 30 items were applied to measure students' motivation and learning strategy. To ensure that the MSLQ instrument fits well with *Crystal Island* game content, the selected 30 items were reworded and tested on a modified 7-point Likert scale (0 = *strongly disagree*, 1 = *disagree*, 2 = *somewhat disagree*, 3 = *somewhat agree*, 4 = *agree*, 6 = *strongly agree*). It was hoped that the re-wording of the items and the revision of the rating format was age-appropriate and closely resembled the original MSLQ. Further, in order to develop the composite variables of students' motivational orientations and learning strategies, a principal component analysis was conducted via SPSS version 27 software to identify the components underlying the modified Motivation and Learning Strategy Questionnaires (MSLQ).

Results obtained from the principal component analysis and the reliability test showed that three components, under the motivation construct, were identified as: *self-efficacy-for-learning-and-performance* (Cronbach's alpha = 0.85), *task value* (Cronbach's alpha = 0.71), and *performance goal-orientation* (Cronbach's alpha = 0.82). Another set of three components were identified under the learning strategy construct, and they were labeled as *SRL_1, SRL_2*, and *SRL_3* (Cronbach's alpha values of 0.70, 0.70, and 0.63, respectively). *SRL_1* demonstrated two aspects of learning strategies such as elaborating learning materials and effort regulation. *SRL_2* had a focus on learning material evaluation, and *SRL_3* demonstrated the use of 'help-seeking' strategies.

Table 1
To solve Crystal Island mystery, students need to engage the following tasks:

Stage-1	Generate hypotheses via the use of gathered evidence, such as reading books/research articles, viewing posters, and conversing with virtual characters to collect illness symptoms and evidence causing illness.
Stage-2	Generate and differentiate provisional diagnosis by running laboratory tests, which include activating a scanning device, selecting scan options, and scanning the contaminants.
Stage-3	Complete the diagnostic worksheet to make final diagnostic decisions and recommend a treatment plan for the patients.

4.3.2. Crystal Island log trace data

Apart from the use of students' self-report data, computer log trace data were also applied to address the research inquiry of the present study. Computer log is a data collection method that automatically captures the action type, content, and time of interaction while a user interacts with a computer system. Logs generally involve time-marked lines of data, which can help inform how individuals navigate learning environments, and how their response sequences take during tasks [19,59,60]. Different from self-reported data that relies on participants' recalls, perception and/or beliefs, computer trace data reflects immediate behavioral executions of mental activities because they are collected unobtrusively during the execution of a learning activity in real-time [61]. Studies in intelligent tutoring research and mass online learning, for example, have suggested that computer log data provide a broad scope of information that can be used to trace learners' cognition-metacognition processes and learning trajectories [9,62–64]. Empirical findings have indicated that log data can better represent children's motivation and goal orientation in comparison to the self-reported data in game-based learning [65].

In this study, log trace data were collected via the *Crystal Island* game system. In *Crystal Island*, participants were asked to engage in a series of activities that include forming testing hypotheses and making diagnoses based on the evidence gathered from completing a series of tasks, such as: reading scientific information from books/research articles, viewing conceptual posters, conversing with virtual characters, running laboratory tests to identify the spreading disease transmission sources, and making final treatment decisions. *Crystal Island* log-trace data is a time-stamped record of every keystroke and mouse click made by participants when interacting with each game element in *Crystal Island*. The total number of mouse clicks for each participant ranged from 546 to 1, 330 and the amount of time spent on each learning activity also varied. Participants' in-game problem-solving behaviors were coded based on three problem-solving stages: *generating initial hypothesis, generate-and-differential provisional diagnosis*, and *final diagnostic decision-making* (see Fig. 1). These problem-solving behavioral variables are task specific. We intentionally extracted and coded the data based on participants' engagement on a particular learning task during their journal to achieve the epic win—solving the *Crystal Island* mystery. Past literature has suggested that context-specific indicators are better predictors of academic success, as compared to generic indicators [66]. In the same vein, we would assume the use of task-specific indicators in our study could minimize the confounding of gaming behavior—an attempt to exploit properties of the game system (feedback, prompts) to succeed in gameplay without learning the material [67,68] and off-task distractions— engaging in activities that do not involve in productive learning [69,70].

Below is the list of variables that were extracted from the *Crystal Island* trace data. Specifically, these were temporal feature variables (i.e., the amount of time spent on interacting with each learning task) and frequency-focused variables (i.e., how often a participant interacted with game elements at each stage of the problem-solving). For example, we operationalized the *initial-hypothesis-generating* activity as the total time that a participant spent:1) comprehending scientific information by reading books, 2) reading conceptually synthesized posters and, 3) conversing with virtual characters for information. Time spent on reading comprehension denotes the time span between a participant opened a book and the time they closed the book. Total time on reading task was calculated based on time spent on each book multiplied by the number of books that a participant completed. We applied the same approach to calculate time on posters and time in conversation with virtual characters (see Table 2).

Interaction frequency indicates how frequently a participant interact with a task during the period from the first action to the end of the task, such as the number of books or posters a participant opened and closed.

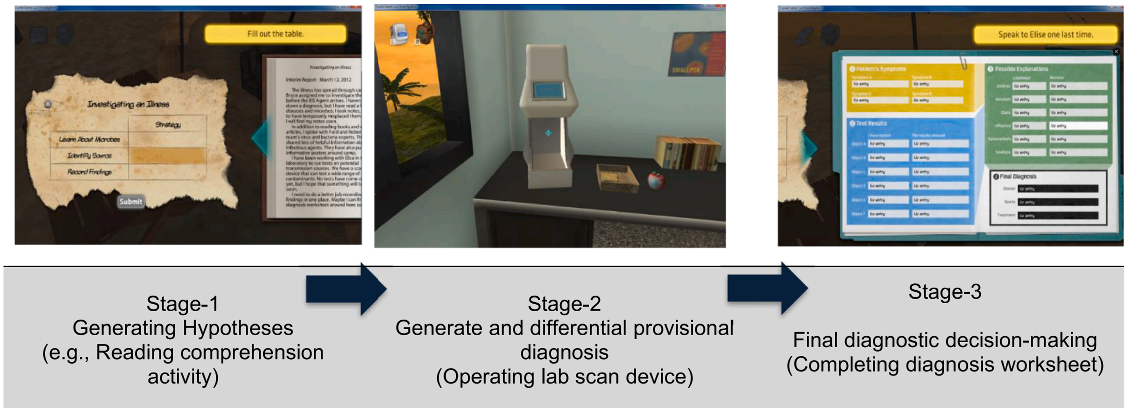

Fig. 1. Screenshots of learning activity at each stage of problem-solving in *Crystal Island*. VCs mean virtual characters.

Table 2
List of learning behaviors variables extracted from *Crystal Island* log trace data.

Stage of Problem-solving	Engagement Measures	Task Behavior/Performance Variables
Generating initial Hypothesis	◆ Measure of Time	Time spent on a book to comprehend scientific information Time spent on answering in-game quizzes Time spent on viewing poster(s) Time spent on conversing with virtual character(s)
	◆ Measure of Frequency	Number of books/research papers being viewed Number of quizzes being completed Number of poster(s) being viewed Number of virtual character(s) being activated
Generate & differential provisional diagnosis	◆ Measure of Time ◆ Measure of Frequency	Time spent on lab tests Frequency of scan device being operated Frequency of scan option(s) being selected
Final diagnostic decision-making	◆ Measure of Time ◆ Measure of Frequency	Time spent on filling out diagnostic worksheet Frequency of the diagnosis worksheet being filled-out and edited
***Hint Usage** includes interacting with virtual characters and posters.*		

Note: These learning behavior variables were extracted from *Crystal Island* log-file trace data and were coded and categorized based on the stages of problem-solving. Both time- and frequency- measures were applied to assess these learning behaviors.

As suggested in the educational data mining literature, both temporal and frequency features are often used to partition trace data in studies on learner behavior (for a review, see [66,70,71]. In this study, these variables were treated as operational indicators of learning behaviors, because they are indicative of the extent to which a participant engages in solving problems within *Crystal Island*.

5. Results

Q1: What can be identified as highly engaging tasks when students interact with Crystal Island to solve scientific problems?

Results from descriptive statistics show that students spent an average of 1132.97 s (approximately 19 min) on reading comprehension tasks, which accounts for 46% of their problem-solving time within *Crystal Island*. They also spent a great amount time conversing with virtual characters ($M_{\text{seconds}} = 396.82$, $SD = 91.38$), running laboratory tests ($M_{\text{seconds}} = 271.17$, $SD = 142.93$) and completing diagnostic worksheets ($M_{\text{seconds}} = 199.95$, $SD = 115.67$). Thus, the in-game reading comprehension task is considered as the most engaging learning activity, as students spent most of their problem-solving time on this task (see Fig. 2.).

Furthermore, according to results obtained from the frequency measure of student interaction with in-game learning elements, both conversing with virtual characters ($M_{\text{frequency}} = 39.56$, $SD = 10.13$) and running the scanning machine to test for the origin of the diseases in the laboratory ($M_{\text{frequency}} = 39.92$, $SD = 24.69$) can be treated as highly engaging learning activities (see Fig. 3). Working on the diagnostic worksheet ($M_{\text{frequency}} = 25.29$, $SD = 14.60$) can also be considered as a somehow engaging learning activity. On the contrary, students were less likely to interact with posters because the number of attempts made to activate the posters was quite low ($M_{\text{frequency}} = 7.77$, $SD = 4.26$).

Q2: What in-game behaviors best predict successful performance in solving scientific problems in Crystal Island?

Before identifying the key in-game behaviors that best predict student problem-solving achievement performance in *Crystal Island*, mean comparison tests were conducted to explore to what extent in-game behaviors differ between students who successfully solved the problems and students who did not solve the problems. As shown in Table 3, successful *Crystal Island* problem-solvers spent much more time viewing posters and talking with virtual characters as compared to students who did not solve the problems. They also spent approximately twice the amount of time to complete the diagnostic worksheet as compared to students who did not solve the problems. However, both groups spent roughly the same amount of time on the reading comprehension activity and operating the laboratory scan device to test their hypotheses.

Concerning the frequency measure related in-game behaviors, the results suggest that successful problem-solvers make slightly more efforts than non-successful problem-solvers with regards to completing in-game quizzes, viewing posters, conversing with virtual characters, and interacting with the scan machine in the laboratory. However, successful problem-solvers far outperformed non-successful problem-solvers in terms of the amount of effort made to work on the diagnosis worksheet.

In addition to the mean comparison tests, two logistic regressions were conducted separately via SPSS version 27 software to assess the power of students' in-game behaviors on their achievement performance of problem-solving with *Crystal Island*. Findings from the first logistic regression analysis, as shown in Table 4, showed that *time-spent-on-the diagnostic-worksheet* significantly contributes to the success of *Crystal Island* problem-solving (Waldχ^2 (1) = 9.39, $p = .00$). Cox and Snell's R^2 and Nagelkerke's pseudo R^2 values of 0.36 and 0.50 indicate a moderately strong relationship between the predictor and the outcome variable. The odds ratio indicates that one-unit increase in the time spent on the diagnostic worksheet, students are 1.02 times more likely to solve

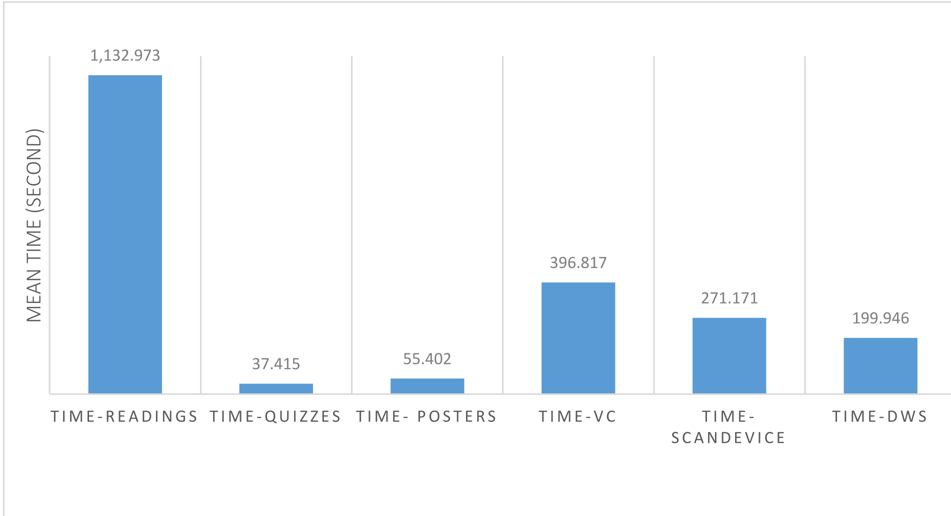

Fig. 2. Time spent on each learning element in *Crystal Island*.

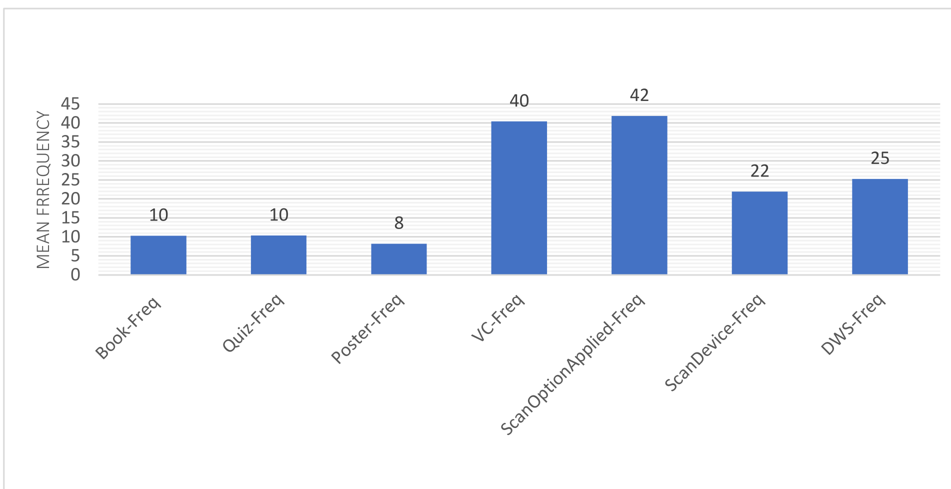

Fig. 3. Frequency of interacting with each learning element in *Crystal Island*.

Table 3
Comparing in-game behaviors between two problem-solving achievement groups.

Crystal Island Problem-solving Achievement		Time-DWS	Time-ScanDevice	Time-VCs	Time-Posters	Time-InGame Quiz	Time-Readings	
Losing	*Mean*	145.77	272.59	386.46	49.71	39.48	1161.57	
	SD	117.71	156.53	95.37	31.28	13.94	388.17	
Winning	*Mean*	302.29	268.49	415.69	71.67	37.41	1132.97	
	SD	102.12	115.11	87.46	31.97	12.32	366.46	
		Frequency-DWS	Frequency -ScanDevice	Frequency-ScanAction	Frequency-VC	Frequency-Poster	Number-InGame-Quiz Taken	Number of Readings
Losing	*Mean*	18.96	20.65	19.06	37.97	6.44	10.00	6.44
	SD	14.74	14.31	13.47	10.64	3.62	2.51	3.63
Winning	*Mean*	34.78	21.33	19.22	42.56	10.28	11.33	10.28
	SD	7.72	9.90	8.90	8.58	4.34	1.78	4.34

the problems in *Crystal Island* ($e^{.02} = 1.02$).

Results from the second logistic regression analysis suggested a strong relationship between in-game behavior (frequency measure; see Table 5) and student achievement in problem-solving (chi-square = 27.97, $df = 6$, $p < 0.001$), according to Cox and Snell's R^2 value of 0.44 and Nagelerke R^2 value of 0.6. More specifically, based on the Wald criterion, four in-game behaviors can significantly predict the success of *Crystal Island* problem-solving, and they are *frequency-of-posters-viewed* (Waldχ^2 (1) = 4.68, $p = .03$), *frequency-of-selecting-scan-options* (Waldχ^2 (1) = 3.96, $p = .047$), and *frequency-of-diagnostic-worksheet-activated* (Waldχ^2 (1) = 6.98, $p = .008$). The odds ratios suggest that one-unit increase in the frequency of activating posters, students are 1.30 times

Table 4
Logistic regression to examine the power of in-game behavior in predicting problem-solving outcome (Using *time*-measure operational indicators).

Stages of Problem-Solving	Predictors	*B*	*β(S.E.)*	*Wald's* χ^2	*p*	e^{β}
	Constant	−1.45	2.33	.39	.53	.23
Generate initial hypothesis	Time spent on readings	.00	.00	.05	.82	1.00
	Time spent on all in-game quizzes	−0.06	.05	1.52	.22	.94
	Time spent on viewing posters	.01	.01	.52	.47	1.01
	Time spent on talking to VC	−0.00	.01	.32	.57	1.00
Generate & differential provisional diagnosis	Time spent on scan device	.01	.01	.44	.51	1.01
Final diagnostic decision-making	Time spent on all DWS	.02	.01	9.39	.00	1.02

Note: −2 log-likelihood: 44.93, Cox & Snell $R^2 = 0.36$, Nagelkerke $R^2 = 0.50$. All the predictors are operational indicators of learning behavior. VC: virtual characters; DWS: diagnostic worksheet.

Table 5
Logistic regression to examine the power of in-game behavior in predicting problem-solving outcome (Using *frequency*-measure operational indicators).

Stages of Problem-Solving	Predictors	*B*	*β(S.E.)*	*Wald's* χ^2	*p*	e^{β}
	Constant	−4.54	2.66	2.91	.09	.01
Generate initial hypothesis	Number of in-game quiz taken	.68	.31	4.71	.03	1.98
	Frequency of posters viewed	.26	.12	4.68	.03	1.30
	Frequency of talking to VC	−0.00	.05	.00	.75	1.00
Generate & differential provisional diagnosis	Frequency of scan device visited	.54	.30	3.28	.07	1.72
	Frequency of scan option applied	−0.31	.16	4.00	.05	.73
Final diagnostic decision-making	Frequency of DWS Activated	.11	.04	6.98	.01	1.12

Note: −2 log-likelihood: 35.55, Cox & Snell $R^2 = 0.44$, Nagelkerke $R^2 = 0.60$. All the predictors are operational indicators of learning behavior. VC: virtual characters; DWS: diagnostic worksheet.

likely to solve the problems in *Crystal Island* ($e^{.26} = 1.30$, see Table 5. When there is a one-unit decrease in the frequency of selecting the diagnostic options in the scan machine, students are 0.73 times more likely to succeed in problem-solving. Students are 1.17 times more likely to solve the problems when there is a one-unit increase in the frequency of activating diagnostic worksheet ($e^{.11} = 1.12$).

Q3: Is there a relationship between students' psychological traits and their in-game behaviors?

Correlation analyses were conducted to examine the relationships between student psychological traits and their in-game behaviors. The results showed that students' *self-efficacy of learning and performance* highly correlated with their engagement in hypothesis testing ($r = 0.29$, $p < .05$). That is, students with a high level of self-efficacy were highly engaged in running the laboratory scan device to test their hypotheses. Students with a high level of prior knowledge also were highly engage when operating the scan device to test hypotheses *(*$r = 0.37$; $p < .01$). However, they were less interactive with reading comprehension activity (time-spent-on-reading: $r = -0.31$, $p < .05$). On the other hand, we also observed that students' *task value* was significantly associated with the reading comprehension activity. More specifically, students with high task value read less books or research articles ($r = - 0.34$, $p < .05$) while solving the problems in *Crystal Island*. Nevertheless, they tended to spend more time on reading books and research articles ($r = 0.31$, $p < .05$).

Further, the results indicated a significant correlational relationship between *'help-seeking' strategies* (*SRL_3*) and in-game virtual characters and posters. That is, students with strong help-seeking learning strategies were highly interactive with virtual characters (time-talk-to-virtual-characters: $r = 0.34$, $p < .05$; frequency-of interacting-with-virtual-characters: $r = 0.27$, $p < .05$). Students who demonstrated strong help-seeking learning strategies were highly interactive with posters (time-spent-on-posters: $r = 0.30$, $p < .05$; frequency-of-activating-posters: $r = 0.28$, $p < .05$). In addition, students with a high level of prior knowledge were also interactive with virtual characters (time-talk-to-virtual-characters: $r = 0.30$, $p < .05$; frequency-of interacting-with-virtual-characters: $r = 0.37$, $p < .01$). In *Crystal Island*, the role of virtual characters is to offer instruction prompts and explanation or to provide feedback. Posters contain key concepts that summarize the causes and symptoms of infectious diseases.

6. Discussion

In this study, a combination of self-report surveys and computer log trace data were applied to examine the psychological mechanisms underlying students' in-game behaviors, and to identify prominent markers of optimal problem-solving performance in an educational video game. Learning in digital environments involves multi-layered interactions that require complex coordination of cognitive resources [72]. Therefore, the analysis of multiple data sources would allow us to have a better understanding of students' learning processes and their individual learning characteristics, such as how students make use of game features, leverage in-game information, and use appropriate strategies to solve problem scenarios in digital games.

Our first research question was concerned with what learning activities were most highly engaging to students. It was found that students were most engaged with virtual characters, with tasks of reading comprehension, and with running the laboratory machine to identify disease transmission sources. The finding that students were most engaged with virtual characters is aligned with previous research, as the reason for using digital games as learning tools is their ability to engage and motivate students for relevant learning [73]. It is also consistent with Vygotsky's pedagogical theories that highlight the importance of social aspects of successful learning (c.f. Vygotsky [74]). In *Crystal Island*, virtual characters provide participants with useful information via dialogues to help players understand nuances within the game, such as patients' symptoms and, helping participants deduce what illness the patients are suffering from. Without interacting socially with characters, players had a much lower chance of successfully solving the problems and completing the game. The finding that students engaged with specific game features (i.e., reading comprehension task and running laboratory tests) is very well established in the field because they support learning goals [22]. The learning focused activity of reading comprehension may be favored because students can work towards goals, monitor their progress on the task, and evaluate their learning progress. The purpose of running laboratory tests is to generate and differentiate provisional diagnoses by operating the scan device to test contaminated food resources gathered from various places in the game. This process typically involves information integration and diagnostic reasoning. Further, our findings conform to prior research showing that a player tends to be more engaged working towards achieving a goal when they have a sense of what game features can help them to moving towards that goal [22]. The level of students' interaction with virtual characters (seeking for instruction/ feedback purposes), the reading materials (acquiring scientific knowledge), and the laboratory equipment to run tests (gathering and integrating information) could demonstrate their sense of agency and control over the gameplay. Both agency and control are the key motivational features of video game to sustain engagement and enhance learning [26,27]. Nevertheless, it is important to note that students' engagement with *Crystal Island* was operationalized via behavior indicative of participation, that is, time on tasks and frequency of interacting with tasks. The use of such unidimensional metrics to assess students' engagement could prevent us from capturing the complex, multi-dimensional nature of engagement. Therefore, caution is needed when interpreting our results and make recommendations for future research in this area.

Our second research question examined what in-game behaviors would best predict successful performance in solving the scientific problems in *Crystal Island*. It was found that successful problem-solvers spent much more time to view posters and converse with virtual characters in comparison to students who did not solve the problems. Furthermore, the successful problem solvers also spent approximately twice the amount of time completing the diagnosis worksheet as compared to students who did not solve the problems. These findings could indicate that students who understood what is required to be successful in the game led to better performance. This increased understanding could attribute to high levels of engagement with each task, where students were more often engaged with information that was interesting. For example, reviewing posters is a way to synthesize key concepts that summarize the causes and symptoms of infectious diseases. The process of completing a diagnosis worksheet is a process of induction and sense-making. To be able to submit a correct diagnostic worksheet, students need to demonstrate an explicit understanding of the transmission sources of the spreading disease. Note that a medical diagnosis requires seeing connections among elements of a situation [75], the more integration of information students aim to generate, the better decision-making they can enlist to treat patients in *Crystal Island*. Moreover, interacting with posters and virtual characters, can also be viewed as a "help-seeking" behavior. A learning behavior, according to Pintrich's definition of self-regulated learning [33], involves the use of organizational and elaborative strategies to comprehend or memorize complex scientific information. Help-seeking is one of the key self-regulatory skills [42,39]. A large body of literature has shown that help-seeking enhances learning and achievement performance [39,46, 49,76]. Our results revealed a direct link between help-seeking behavior and students' success in problem-solving with *Crystal Island*.

Finally, we were interested in understanding the relationship between student psychological traits and in-game behaviors. Findings indicated that students, with high self-efficacy, were highly engaged in running the laboratory scan device to test their hypotheses. Students with a high level of prior knowledge were highly active when operating the scan device to test hypotheses. However, those students who had high self-efficacy spent less time interacting with the reading comprehension task. While this may seem problematic, the reading comprehension activities did not, in fact, help facilitate winning in the game. The activity itself is designed solely for learning and practicing of reading comprehension and is not related to winning the game. As such, it is possible that students who were less engaged in the reading comprehension activities, but had strong self-regulation skills, had better knowledge of what is required to be successful in the game (i.e., win the game). Further, these students may again hold stronger performance appraisals and feel more agency of their performance due to receiving immediate feedback or scaffolding from the laboratory tasks. Having a high level of prior knowledge may also help students to experience an appropriate level of confidence in relation to their performance. In addition, our result showed that students, with high task values, tend to be more selective in terms of their reading choice (i.e., choosing which book to read), and they tend to engage more deeply in reading those books, as measured by time spent on reading. In academic contexts, engagement is treated as the intensity of cognitive and behavioral involvement, as well as the emotional quality of a person's effort on a task [77,78]. This finding aligns with previous research, specifically a meta-analysis that indicated a significant association between video-gameplay, attention, and cognition [79]. Individuals with stronger cognitive skills are likely to seek out more engaging activities [80]. Therefore, we suspect that students, who had high task values, were actively choosing which book to read and spending more time reading the books due to their more advanced cognitive skills. As such, how much control students believe they have over a task can be reinforced by providing access to additional information (i.e., posters, diagnostic testing) and ability to get help or feedback from virtual characters. Another noteworthy finding of this study is that students with strong help-seeking strategies were highly interactive with virtual characters and with posters. Students with a high level of prior knowledge were also highly interactive with virtual characters. As mentioned previously, both virtual characters and posters are scaffolding tools to support students to solve problem efficiently. Therefore, students had more opportunity to receive feedback on their work by accessing virtual characters more frequently, and as a result, made more effort to complete their diagnostic worksheets. This led to better problem-solving during the gameplay. These findings suggest that students, with strong prior knowledge and self-regulated learning skills, specifically efficient help-seeking behaviors, were more likely to perform optimally and solve problems during their interaction with *Crystal Island*. These students were better able to make use of in-game resources and were more deliberate in their actions when searching for appropriate resources and information to help them solve problems. Therefore, it is plausible for us to consider the combined functioning of both cognitive (e.g., students' prior knowledge and help-seeking strategy) and non-cognitive (e.g., perceived self-efficacy, goal, sense of flow) factors when defining optimal problem-solving pathways in *Crystal Island*. In this study, students who successfully solved *Crystal Island* problems demonstrated multiple characteristics in terms of task engagement and in-game learning behavior. First, they were able to discern key game events and resources management in *Crystal Island*. Second, they were skillful in terms of prioritizing time and effort when navigating the game environment. For example, spending less time on reading comprehension tasks, increasing the frequency of reviewing posters, and conversing with virtual characters. Moreover, these students can be viewed as "efficient, self-regulating help-seekers", because they were not only selective in terms of how and when to get help, but also focused on understanding the principles behind the resolution. For example, they were highly interactive with posters and virtual characters to get "just-in-time" explanations and/or instructional cues to complete the task in question.

These results shed insight on the important role of users' dispositions and their interaction with game design. This is a very promising area of research because of the neglection in literature so far, as suggested in multiple recent review papers on game-based learning [22,81]. Our results indicate that students, with specific individual characteristics (i.e., self-efficacy, prior knowledge) and success-striving in-game behavior, use GBL to promote the development of crucial self-regulated help-seeking behaviors, that are pivotal for optimal problem solving with digital games. By learning users' dispositions, the function of help-seeking, as well as their interaction with game features, digital game systems can adjust the cognitive complexity of learning tasks through instructional approaches, such as delivering timely, relevant feedback to game users to meet their learning needs, thereby, to promote engagement and optimal learning gains.

6.1. Contributions to knowledge

Taken together, the findings of this study not only provide valuable insight into the role of students' individual characteristics and learning behavior in problem-solving processes, but also emphasize the importance of help-seeking behavior in the problem-solving. These factors could be treated as crucial parameters for modeling students' learning and engagement outcomes in open-ended technology-enhanced learning environments. In an open-ended learning space, students can demonstrate a wide range of problem-solving trajectories, which pose a big challenge for instructors and game designers to provide adaptive scaffolding for assisting students to effectively solve the problems. It is hoped that the findings of this study address this knowledge gap. These findings also have important educational implications. By understanding how students make use of in-game features, educational researchers and game developers can use this information to improve task performance and promote success in games. This can be done by using the information to develop scaffolding or instruction tools, such as intelligent artificial characters or instructional prompts/cues, that can facilitate and enrich the interaction between humans and machines in the learning context. These scaffolds from artificial characters may lead the student to engage in more self-regulated help-seeking behaviors thereby increasing optimal learning and successful gameplay. Previous research has found that learning and engagement is highly dependent on the type of feedback learners receive such as immediate feedback and positive feedback [21]. Future research should address scaffold type, and the timing of scaffolds provided by in-game artificial characters, to assess whether the scaffolds can lead to increased effective self-regulatory processes and learning outcomes in the game. This can be used to inform future development of game-based learning environments where the learning system can measure and flag when the player is bored or disengaged, then re-engage the learner in a task that increases interest and cognitive arousal, provides options of choice to increase perceived control, or provides an optimal level of challenge [82]. Overall, the findings of the current study highlight the role of these interactive factors in the process of optimization in problem-solving with *Crystal Island*, and they are: self-efficacy of learning, prior knowledge, the use of effective strategies to support learning, and the appropriate instructional approaches like in-game prompts/scaffolds. To the best of our knowledge, few studies, to date, have taken this approach to examine the interactions between learners' intrapersonal variables and external contextual factors in determining the trajectory of optimal problem-solving. It is hoped that this study can deepen our understanding of the mechanisms and pathways of students' optimal learning in digital game-based learning environments.

To sum up, results from current study indicate that the combined use of self-report surveys and trace data (i.e., trace-measure of engagement) allow us to identify the role of user dispositions in shaping their gameplay experience and highlight the way how self-regulated help-seeking determines optimal problem-solving pathways in digital games. Understanding how learners navigate and interact with digital video games enables us to understand what part of gameplay is progressing well and what is not. We can use this information to create personalized, process-oriented feedback model in digital games to sustain users' engagement and promote deep learning. Feedback is an integral part of digital game as it helps to sustain engagement [83]. The design of effective feedback support and scaffolding system within game-based learning environments is crucial for promoting learner optimal learning experience. In addition, our measure of students' engagement with *Crystal Island* using trace data provide an valuable insight on how to use trace data for real-time modeling of student learning processes. Trace-measure of students' engagement with digital games can help to build learner models that can be used for personalized content generation, difficulty adjustments, and strategy prediction [84].

Our findings also add new perspectives to existing research on self-regulated learning with digital games. For example, our results indicate that students with specific individual characteristics and success-striving in-game behaviors use GBL to promote the development of crucial self-regulated help-seeking behaviors. Digital games provide "situated learning", where problem scenarios mimic real world problems [23] and players are allowed to experiment and construct meaning based on their own experiences [22]. Digital games have great potential for cultivating students' adaptive help-seeking processes and SRL transfer. We hope that future game development will benefit from this work when designing game features that can be used to foster learning and problem solving through GBL.

6.2. Limitations and future directions

Our research results put forth promising avenues for advancements of game-based learning environments, but are subject to certain limitations. First, to assess learning, we examined the learning scores from multiple tasks throughout the gameplay. However, we have only applied the overall problem-solving performance outcome score (i.e., succeed or failed the problem solving with *Crystal Island*) to assess how student in-game behaviors differ between two achievement groups and how this relates to student psychological traits, so that we can identify the emergent markers of optimal problem-solving pathways in the game. While our analysis did adequately address the research inquiry of the present study, it would be important to examine different kinds of learning indicators that reflect the complexity of the learning process during gameplay with *Crystal Island*. In addition, the current study was placed within the context of a narrative-centered video game, the operational indicators of learning behaviors extracted from computer log data are task-specific variables, which may have compromised the generalizability of our findings.

Another limitation of this study relates to time and frequency estimation of students' engagement with *Crystal Island*. Trace data, in recent years, have been extensively used to study student engagement, and engagement is often measured by time on tasks and frequency of interacting with learning activities [59,85]. Nevertheless, the approaches used to estimate time on tasks and frequency of interaction with tasks are determined by the characteristics of a learning environment, and there still lacks consensus in term of how different estimation strategies should be performed [66,70]. Moreover, time-on-task estimation can be biased under the influence of off-task distractions [69]. To this end, we would recommend using caution when interpreting our findings. We would call for refinement in LMS systems of digital educational games where an advanced time-on-task extraction and off-task behavior detection tool needs to be implemented to collect trace data relevant to learning processes.

The third limitation of this study concerns sample-size adequacy relative to the variable-centered, cross-sectional statistical approach applied in the data analysis, as well as the sample diversity in terms of the ratio disparity in participants' age range. Even though our sample population represented an appropriate sample for research on digital game-based learning and aligns with previous empirical studies on game-based learning using *Crystal Island* [53,56], age variation in our sample population may have influenced how students engage with and use help strategies to solve *Crystal Island* mystery. These limitations could pose a threat to the generalizability of our findings. For future work, it is important to have a larger sample size with diverse knowledge backgrounds and more balanced sample sizes across different age groups, so that it can add ecological validity to the results. From a practical perspective, we are interested in communicating with the development team who designed *Crystal Island* game, instructional designers or the like to explore the possibility of designing a system where mechanisms can be used to detect off-task behaviors and extract accurate time-on-task data. We would call for further validating the metrics of trace-measure of students' engagement and learning processes in digital learning environments. For our next step, we plan to implement temporal models of the fine-grained interactions between the learning activity, in-game behaviors, psychological traits, affective states and performance. We believe this will provide valuable information for developing rich scaffolding and feedback frameworks in digital game-based learning environments.

Declaration of Competing Interest

We would like to declare that we do not have any financial and personal relationships with other people or organizations that could inappropriately influence (bias) their work or state.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2022.100117.

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