

Efficiency or Effectiveness in Game-Based Learning: Is Engagement Enough?

Maral Karimi ¹[0000-0002-8258-2547], Megan Wiedbusch ¹[0000-0002-4619-1709], Natalie Blaize ¹[0009-0005-1946-0706], James Lester ²[0000-0003-1481-6601], and Roger Azevedo ¹[0000-0002-5018-6232]

¹University of Central Florida, School of Modeling, Simulation, and Training, Orlando, FL, USA

²North Carolina State University, Raleigh, NC, USA

maral.karimi@ucf.edu

Megan.Wiedbusch@ucf.edu

natalie.blaize@ucf.edu

lester@ncsu.edu

Roger.Azevedo@ucf.edu

Abstract. In STEM education, game-based learning environments (GBLEs) have become prominent platforms to scaffold students’ self-regulated learning (SRL) strategies. This study challenges the assumption that all engagement in GBLEs is equally beneficial by distinguishing cognitive from behavioral engagement within the Integrative Model of Multidimensional SRL Engagement (IMMSE). We analyzed data from 227 high-school students playing Crystal Island, a narrative-centered microbiology GBLE, to examine how these engagement types during the forethought and performance SRL phases predict learning gains and problem-solving accuracy. Overall, results showed that cognitive engagement significantly predicts learning gains, whereas behavioral engagement does not. This result supports IMMSE’s distinction between surface-level actions and deeper processing, indicating that meaningful learning depends on strategic cognitive engagement. We discuss implications for designing adaptive scaffolds that dynamically balance engagement dimensions across early SRL phases to optimize both efficiency and effectiveness.

Keywords: Engagement, Self-Regulated Learning, Game-based Learning Environments, STEM, Log Files.

1 Introduction

Game-based learning environments (GBLEs) are increasingly used to develop students’ complex cognitive and metacognitive STEM skills [1]. These environments are often recognized for their capacity to engage learners through immersive narrative-centered stories, interactive problem-solving, and instant feedback [2]. While engagement is frequently seen as a key factor in successful learning, studies show that it comprises different types (i.e., cognitive, affective, behavioral, and agentic), and that not all are equally helpful; moreover, time spent actively “engaged” may not always lead to meaningful learning improvements [3,4]. As researchers and designers work on designing GBLEs, it becomes important to ask whether increasing engagement alone is enough or if it needs to be balanced with other learning goals such as efficiency (e.g.,

optimal time-on-task, strategy use) and effectiveness (e.g., learning improvements, transfer of learning). Finding this balance is essential for designing thoughtful GBLEs that are truly effective in education [5]. This paper investigates whether learners who appear highly cognitively and behaviorally engaged within GBLEs are also learning effectively. Drawing from research in GBLEs, self-regulated learning (SRL) and engagement, we argue that optimal learning in GBLEs requires more than sustained interaction; it requires learners to strategically allocate cognitive resources and to adaptively engage both cognitively and behaviorally with tasks throughout the different SRL phases, supporting both efficient and effective learning.

2 Prior Work

Self-regulated learning (SRL) is learners' ability to actively monitor and regulate their own cognitive, affective, metacognitive, and motivational processes to achieve a goal across three phases (i.e., forethought, performance, and self-reflection) [6-10]. Researchers have designed GBLEs [1] to foster effective SRL using a range of game features that influence learners' engagement and interest in learning, by leveraging diverse data sources such as self-report surveys, log traces, and facial expressions [11-14]. Their work highlights that engagement is a multifaceted psychological construct (e.g., behavioral, emotional, agentic, (meta)cognitive) that is difficult to define, measure, and scaffold due to lack of concrete definition and its multiple dimensions [7, 15]. Additionally, while increased SRL engagement is inherently cognitively demanding for learners [16] and difficult to define, measure, and scaffold, it is even more challenging in GBLEs, where immersive game mechanics can disrupt effective self-regulation. GBLEs are open-ended environments, allowing learners to explore freely, but at the expense of scaffolded SRL support [11], underscoring the need for adaptive scaffolds especially early within the SRL phases. While many GBLEs incorporate scaffolding for domain knowledge acquisition [11], few learning environments incorporate scaffolding techniques intended to enhance individual learners' multidimensional engagement during SRL phases that are grounded in theory and data driven [15]. Several studies highlight the impact of early interventions in GBLEs on learners' engagement and efficient learning, showing that learners who are more cognitively engaged during the forethought and performance phases are more likely to set meaningful goals, develop effective plans, and allocate mental effort efficiently [8, 9, 14]. For example, Wiggins et al. [14] found that learners' behaviors and affective states in the tutorial phase explain most variance in engagement and mental demand, marking these early moments as optimal intervention points. Li and Lajoie [17] argue that learners require adaptive scaffolding that helps them strategically manage the different dimensions of engagement, especially across early SRL phases, to optimize learning outcomes [17]. Despite the theoretical and conceptual understanding that supporting engagement within GBLEs should result in more effective and efficient learning, additional research is needed to understand how different phases of SRL (specifically forethought and performance phases), and the multiple dimensions of engagement interact to enhance efficient and effective learning. As such, this study is grounded in Wiedbusch et al.'s [15] Integrative Model of Multidimensional SRL Engagement (IMMSE), which highlights that engagement is not static but dynamic and cyclical, comprising behavioral, emotional, cognitive, and agentic dimensions [19], and

each of these dimensions offers a different lens into learners' engagement behavior in different SRL phases [15]. Specifically we focus on students' cognitive and behavioral engagement during the forethought and performance SRL phases and their relationship to learning gains and problem-solving accuracy while using Crystal Island, a narrative-centered GBLE, to learn high-school microbiology [12], to contribute to the development of intelligent scaffolding systems that support individual learners' needs while maintaining a balance of cognitive and behavioral engagement while optimizing learning efficiency [20].

3 Theoretical Framework: An Overview of the Integrative Model of Multidimensional SRL Engagement (IMMSE)

Because engagement is a complex construct, it has been defined in several ways. SRL and student engagement are distinct but complementary research domains that both seek to understand how students function and perform academically [21]. To deepen our understanding of effective and efficient learning, researchers have explored how SRL phases interact with different dimensions of engagement, rather than viewing one as a subset of the other [17]. Pintrich and de Groot [22] identified cognitive strategies, effort management, and metacognitive strategies as key SRL components that align with cognitive engagement. Cleary and Zimmerman [18] linked SRL to cognitive engagement through a self-regulatory engagement framework. Li and Lajoie [17] advanced this by introducing the Integrative Model of SRL Engagement, which adds strategic and effort planning to the forethought phase for a more nuanced view of cognitive engagement. Building upon their model, the Integrative Model of Multidimensional SRL Engagement (IMMSE) [15] further advances our understanding by integrating emotional and behavioral engagement in addition to cognitive engagement based on the work of Reeve [19]. Wiedbusch et al. [15] propose that engagement is a multidimensional construct, comprising behavioral, emotional, cognitive, and agentic dimensions that all fluctuate dynamically across SRL phases [19]. Within this model, *behavioral engagement* refers to actively using learning strategies and maintaining attention, effort, and persistence to stay on task [23]. *Cognitive engagement* involves strategic thinking and the mental effort invested across a task continuum [17]. *Emotional engagement* captures affective states, like curiosity or anxiety, that influence learning processes [24]. *Agentic engagement* includes learners' proactive contributions, such as asking questions and modifying goals [24]. Moreover, they [15] argue that behavioral engagement, like paying attention or staying on task, must be visible, but this isn't necessarily true for the other dimensions of engagement. For instance, a learner may appear behaviorally engaged; however, this does not necessarily reflect cognitive engagement. The IMMSE model clarifies this difference and separates strategy use from cognitive engagement and argues for the potential regulatory and reciprocal nature between cognitive engagement and behavioral engagement. This model assumes engagement is dynamic across the various SRL phases. Specifically, in the forethought phase, learners initiate task analysis and goal setting, which activates cognitive engagement as they determine strategies and allocate effort. As learners transition to the performance phase, they enact and monitor the strategies they planned. According to the IMMSE, cognitive efficiency is central to effective and efficient learning within GBLEs. Learners must decide how to allocate

and sustain mental effort strategically [15]. Thus, sustaining cognitive engagement across the forethought and performance phases is essential for meaningful strategy use during learning. This model also includes a self-reflection phase, in which learners evaluate their performance and progress to inform future learning [15]. We do not examine this phase, focusing instead on the role of engagement in the forethought and performance SRL phases within GBLEs, where instructional interventions can most effectively promote efficient and effective learning [18]. We also exclude agentic and emotional engagement because IMMSE positions cognitive and behavioral dimensions as the primary dimensions for goal setting, strategy execution, and effort maintenance, which affect learning gains and problem-solving performance. Although the IMMSE has not yet been empirically tested, with this study representing one of the first applications, it builds upon and synthesizes empirically supported components of SRL and engagement research.

4 The Present Study

In this study, we investigated whether in-game cognitive and behavioral engagement actions during the forethought and performance SRL phases influence learners' learning gains and problem-solving accuracy (i.e., measures of GBLE effectiveness), and game-solve time (i.e., a measure of GBLE efficiency) in Crystal Island, a narrative based GBLE for high-school microbiology. The following research questions (RQs) guide this study:

RQ1. To what extent does time spent on cognitive and behavioral engagement actions during the forethought and performance phases of self-regulated learning predict participants' learning gains?

RQ2. To what extent does time spent on cognitive and behavioral engagement actions during the forethought and performance phases of self-regulated learning predict participants' problem-solving accuracy?

RQ3. Is there a significant difference in the time spent on cognitive versus behavioral engagement actions during the forethought and performance phases of self-regulated learning?

5 Methodology

5.1 Participants

After excluding 12 participants due to missing data, the final sample included 227 high school students (Mean age = 15 years; 33.5% were female) from southern U.S. schools.

5.2 Measures: Learning Outcomes and Self-Reports

Each student completed 17-item pre- and post-tests on microbiology, with learning measured via normalized learning gains (NLGs). The pre-test included the Achievement Goals Questionnaire [25] and the Junior Metacognitive Awareness Inventory [26], while the post-test included the Intrinsic Motivation Inventory [27] and the Presence Questionnaire [28]. Self-report data were not analyzed.

5.3 Crystal Island Game Environment

Crystal Island is a narrative-centered game-based learning environment developed to support middle school students' scientific reasoning skills in microbiology [12]. This study used the full-agency version, in which learners, as CDC agents, freely explore a first-person simulation to investigate a mysterious research outbreak by identifying the source, diagnosing the illness, and proposing a treatment plan. Players explore island buildings and informational resources, interact with non-playable characters (NPCs), and navigate the environment. Interactive mechanics scaffold problem solving; for example, a diagnosis worksheet enables them to record symptoms. To finish, participants submit the worksheet to the camp nurse. Correct submissions confirm successful mystery resolution; incorrect ones trigger either targeted prompts or more generic feedback when multiple components are wrong, encouraging self-reflective re-exploration. We used the first worksheet submission as a behavioral marker indicating completion of the initial SRL phases (forethought and performance) and transition into the self-reflection phase. We analyzed detailed log files to extract time-based indicators of cognitive and behavioral engagement by aggregating the duration of specific in-game behaviors including reading resources, conversations with NPCs, navigating the island, viewing posters, using the scanner, and reviewing or completing the diagnosis worksheet (see Coding and Scoring; Figure 1).

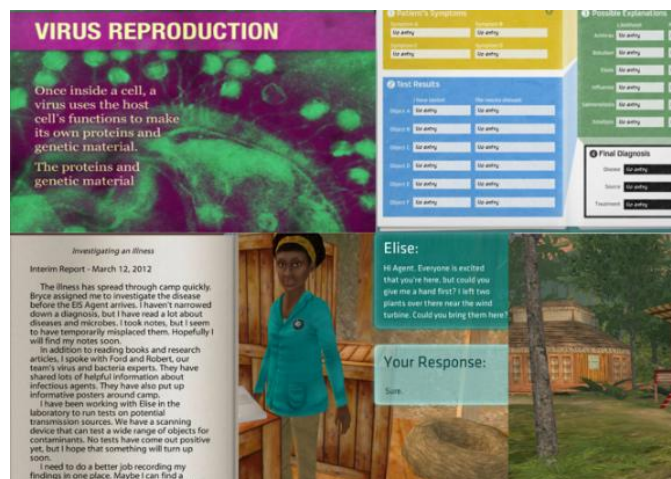


Figure 1. In-Game Behaviors

6 Procedures

After obtaining parental consent and student assent, the study followed three phases: (1) pre-test, during which students completed the microbiology assessment and self-report measures (see above); (2) a gameplay session of up to 60 minutes or until mystery completion on Crystal Island; and (3) post-test, during which they took the microbiology assessment and self-report measures (see above). IRB approval was obtained beforehand, and no participant compensation was provided.

7 Coding and Scoring

7.1 Engagement Actions Gains

We measured participants' engagement during the forethought and performance SRL phases, which occur before participants submit their first worksheet using log files of player actions. Five gameplay behaviors were categorized according to the cognitive and behavioral dimensions of engagement; the proportional duration of each category was calculated by summing all relevant action durations and dividing by the total game time until the first worksheet submission (or the full session if no submission occurred before the end of the time period).

Behavioral engagement actions included movement and conversation. Movement was defined as when a player traveled from one in-game location to another. Conversation referred to interactions between learners with (NPCs), such as scientists or locals on the island.

Cognitive engagement actions included four main actions: reading books and articles refers to opening and engaging with informational texts available within the game, such as scientific guidebooks or educational reading materials, viewing posters by inspecting educational materials like disease charts and pathogen visual guides placed throughout the game., using the worksheet to enter observations, evidence, and hypotheses, and operating the in-game scanner to conduct lab-based analyses by testing suspected contamination sources against pathogens.

7.2 Normalized Learning Gains & Solving the Mystery

Normalized learning gains (NLGs) were calculated using Marx and Cummings's [29] normalized change score equations, which account for prior knowledge when comparing pre- and post-test microbiology quizzes. Participants' NLGs averaged 0.12 ($SD = 0.35$), and 98 of 227 (43%) participants solved the mystery within 60 minutes.

8 Results

8.1 Research Question 1

A multiple linear regression was conducted to examine whether proportional time spent on cognitive and behavioral engagement (relative to total game time to the first worksheet submission) actions predicted participants' learning gains. The overall model was significant, $F(2, 224) = 8.37, p < 0.001, R^2 = 0.07$. Time spent on cognitive engagement was a significant positive predictor of learning gains, $\beta = 0.64, SE = 0.16, t(224) = 4.09, p < 0.001$. Time spent on behavioral engagement did not significantly predict learning gains, $\beta = 0.12, SE = 0.12, t(224) = 1.01, p = 0.32$. That is, holding time spent on behavioral engagement constant, for every one-unit increase in time spent on cognitive engagement, learning gains increase by 0.64 units. This result suggests that enhancing cognitive engagement is more impactful for learning than emphasizing behavioral actions.

8.2 Research Question 2

A binary logistic regression was conducted to examine whether proportional time spent on cognitive and behavioral engagement actions (relative to total game time to the first worksheet submission) during the forethought and performance phases predicted the odds of successfully solving the mystery. The overall model was not significant, $\chi^2(2, N = 227) = 3.64, p = .162$ (Nagelkerke $R^2 = .012$), indicating that time allocation on cognitive versus behavioral engagement actions did not reliably predict learners' accuracy in solving the mystery. This result highlights the need to investigate additional factors such as strategy effectiveness or contextual task demands to predict problem-solving success.

8.3 Research Question 3

Before conducting the analysis, we tested the assumption of normality for the difference scores (cognitive – behavioral) of the proportional time spent on engagement activities (relative to total game time to the first worksheet submission) using the Shapiro-Wilk test, which revealed a significant departure from normality ($p < .001$). Due to this violation, we used a non-parametric Wilcoxon signed-rank test which revealed a significant difference between cognitive and behavioral engagement times, $W = 9413.0, p = .0004$. On average, participants spent more time on cognitive engagement ($M = 0.429, SD = 0.149$) than on behavioral engagement ($M = 0.380, SD = 0.191$). This suggests that students allocate more of their early gameplay time to cognitively demanding actions, such as reading and analyzing (e.g., evaluating scanner or poster data).

9 Discussion

Our study examined differences in how learners engaged in behavioral and cognitive engagement actions during GBL and their impact on learning and performance outcomes. We found that while time spent on behavioral engagement did not significantly predict learning gains, time spent on cognitive engagement did. However, neither behavior was predictive of solving the mystery. These results provide empirical support of the IMMSE model [15], which distinguishes between the appearance of engagement and its deeper cognitive quality. Although behavioral engagement was visible, it did not significantly predict learning gains, suggesting that surface-level actions are not sufficient for meaningful learning. According to the IMMSE model, impactful engagement arises when cognitive engagement regulates behavioral actions. These findings also highlight that learners have two goals in Crystal Island: understanding microbiology and solving mysteries. While learning might require deeper cognitive engagement with the game, problem-solving performance (i.e., GBLE effectiveness) may hinge less on this requirement and more on strategic efficiency through hypothesis testing or trial-and-error strategies. Some successful students may have relied on intuitive guessing rather than deep conceptual understanding, resulting in solving the mystery but not learning. Less successful learners may have focused heavily on information gathering without effectively applying it, learning more but failing to solve the mystery. Our study also found a difference between time spent on

cognitive and behavioral actions, with learners spending more time on cognitive engagement. These findings offer important insight into how learners allocate their limited (meta)cognitive resources during early gameplay. Specifically, it suggests a cognitive trade-off in which learners devote more time to mentally demanding activities, which may result in a reduction of their exploratory or interactive behaviors. From an IMMSE perspective, future research is needed to test the theoretical assumption that engagement dimensions are dynamically regulated. Our study has highlighted that they appear differently within the first two phases of SRL. That is, learners do not simply engage in more or less overall but instead may shift engagement types based on evolving goals, task demands, and available cognitive resources. In open-ended, narrative-driven environments like *Crystal Island*, learners must choose how to explore, gather, and process information, which can accentuate these trade-offs. For example, spending more time on cognitive engagement during the earlier phases of learning might reflect an intentional focus on the goal of learning science content. Conversely, spending more time on behavioral engagement actions may not have been strategic but instead reflect goal ambiguity or superficial exploration. This would align with prior research that suggests behavioral engagement actions may not promote learning [3, 13]. However, distinguishing cognitive from behavioral engagement using log data alone is challenging, and additional evidence (e.g., eye-tracking to capture attention patterns) may be needed to clarify this differentiation. Our study not only provides empirical evidence for the IMMSE model by finding a distinction between engagement type and strategy use, but it also supports the assumption that one type of engagement may not be better. Ultimately, it is the type, timing, and coordination of engagement dimensions that matter. While our interpretation aligns with IMMSE, other alternative explanations must be considered. For example, learners' prior knowledge may have shaped engagement patterns. Differences in motivation and goal-orientation could also explain variations, with performance-oriented students may have prioritized solving the mystery, while mastery-oriented students invested more time in learning about the content. Additionally, the design of *Crystal Island* may itself encourage exploratory actions that are not tightly coupled with deeper processing. GBLEs, therefore, should aim to support learners in making strategic decisions about how and when to engage cognitively versus just behaviorally.

10 Future Directions

The future of game-based learning research must move beyond simple engagement metrics and focus on developing validated instruments that can distinguish between cognitive and behavioral engagement with other dimensions of engagement (i.e., affective and agentic) in real-time during gameplay. This will require the integration of multiple sources of data, including well-timed administration of self-reports (e.g., at the beginning, middle, and end of the forethought and performance phases of SRL) with continuous multimodal data in real-time during gameplay. Future research on efficiency and effectiveness in game-based learning should explore the nuanced interplay between cognitive and behavioral engagement and their impact on learning outcomes. Researchers should design studies that distinguish between surface-level behavioral metrics and sophisticated cognitive and metacognitive processes. Another key direction involves developing and testing adaptive GBLEs that dynamically balance efficiency

(e.g., time to mastery, reduction of redundant activities) and effectiveness (e.g., conceptual understanding, transfer of skills) using real-time engagement diagnostics. Finally, individual learner characteristics such as prior domain knowledge, metacognitive ability, motivation, and even personality traits must be considered to examine the efficiency-effectiveness-engagement relationship.

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