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In-Game Actions to Promote Game-Based Math Learning Engagement

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Abstract

Game-based learning (GBL) has increasingly been used to promote students' learning engagement. Although prior GBL studies have highlighted the significance of learning engagement as a mediator of students' meaningful learning, the existing accounts failed to capture specific evidence of how exactly students' in-game actions in GBL enhance learning engagement. Hence, this mixed-method study was designed to examine whether middle school students' in-game actions are likely to promote certain types of learning engagement (i.e., content and cognitive engagement). This study used and examined the game *E-Rebuild*, a single-player three-dimensional architecture game that requires learners' application of math knowledge. Using in-depth gameplay behavior analysis, this study sampled a total of 92 screen-recorded and video-captured gameplay sessions attended by 25 middle school students. We adopted two analytic approaches: sequential analysis and thematic analysis. Whereas sequential analysis explored which in-game actions by students were likely to promote each type of learning engagement, the thematic analysis depicted how certain gameplay contexts contributed to students' enhanced learning engagement. The study found that refugee allocation and material trading actions promoted students' content engagement, whereas using in-game building tools and learning support boosted their cognitive engagement. This study also found that students'

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learning engagement was associated with their development of mathematical thinking in a GBL context.

Keywords
learning engagement, game-based learning, sequential analysis, thematic analysis

Most primary school students in the United States have encountered challenges with learning math (e.g., arithmetic and geometry; Kebritchi, Hirumi, & Bai, 2010). These challenges likely cause students to experience emotional depression (Hopko, Mahadevan, Bare, & Hunt, 2003) as well as task anxiety (Ashcraft, 2002) in approaching math problems. They also cause students' disengagement (Loong & Herbert, 2012). Research on game-based learning (GBL) has generally stated that high engagement is a key precursor of students' continuous success in learning (Filsecker & Hickey, 2014; Hamari et al., 2016). Researchers explain that learning math through gameplay contributes to students' perseverance by enhancing their learning engagement (Ke, 2008; Tsai, Kuang-Chao, & Hsiao, 2012). Enhancing learning engagement via GBL refers to not only promoting students' perseverance in challenging tasks but also fostering learners' mindful thinking (Huizenga, Admiraal, Akkerman, & Dam, 2009; Plass, Homer, & Kinzer, 2015). Learning engagement indicates students' cognitive awareness of knowledge application with high internal motivation (Abdul Jabbar & Felicia, 2015). Although several researchers attempted to demonstrate the effect of GBL on learning engagement (Hamari et al., 2016; Ke, Xie, & Xie, 2016), the question as to how game design fosters students' learning engagement remains. Although multiple previous studies (Abdul Jabbar & Felicia, 2015; Eseryel, Law, Ifenthaler, Ge, & Miller, 2014; Hamari et al., 2016) have addressed the importance of students' learning engagement in GBL, there is a paucity of research examining specific game features that promote learning engagement. This mixed-method study aims to explore to what extent certain game actions promote learning engagement (i.e., content and cognitive engagement). In this study, we employed a three-dimensional (3D) architecture game *E-Rebuild* that is designed to engage students in architecture-themed mathematical problem solving. To measure associations between game actions and learning engagement, this study adopted multiple data analysis approaches, including sequential analysis and qualitative thematic analysis. The sequential analyses in this study estimated how likely students were engaged in their learning via their in-game actions, while the thematic analysis provided explorative findings of why certain game actions promoted students' learning engagement. Overall, two research questions guided this study: (a) Which in-game actions in a 3D math game are most likely to promote students' learning engagement? (b) What is the relationship among the types of game actions, learning engagement, and the development of mathematical thinking in gameplay?

Literature Review

Learning Engagement in GBL

Researchers have defined learning engagement as a key mediator that bridges learning and motivation (Abdul Jabbar & Felicia, 2015) and an ongoing condition in which a learner pays full attention to learning tasks (Ke et al., 2016). Research also states that learning engagement leads to students' growth of internal motivation with subject matters longitudinally (Bodovski & Farkas, 2007). Generally, learning engagement in GBL refers to the participatory mind-set for acquiring desired goals (Eseryel et al., 2014). The definitions of learning engagement in the literature on GBL vary. While some researchers state that engagement indicates playfulness (Bai, Pan, Hirumi, & Kebritchi, 2012) and enjoyment (Hainey, Boyle, Connolly, & Stansfield, 2011), others focus on learners' cognitive reflection (Huizenga et al., 2009), including metacognitive skills (Plass et al., 2015). Early motivation theories have speculated how a game stimulates learners' engagement (Boyle, Connolly, & Hainey, 2011; Farrell & Moffat, 2014). Furthermore, research on self-determination theory depicts engagement with three key driving factors (i.e., autonomy, competence, and relatedness). The interplay among these three factors is deemed significant in explaining how students become engaged by satisfying fundamental human needs (Przybylski, Rigby, & Ryan, 2010).

Early researchers have considered engagement as an essential element of self-regulated learning, which focuses on students' motivated actions on their learning. Plass et al. (2015) classified four types of learning engagement: cognitive, affective, behavioral, and sociocultural engagement. Among these types of engagement, their study reports that cognitive engagement is highly related to students' mental processing with high metacognition. They also report that cognitive engagement is the variable that most reliably predicts students' effective problem-solving actions aiming at their learning goal. Similarly, Ke et al. (2016) stated the two types of learning engagement as content and cognitive engagement. They primarily addressed the nature of learning engagement regarding students' problem-solving skills and content knowledge acquisition. While content engagement represents the way in which learners apply procedural and conceptual knowledge only through game requests, cognitive engagement refers to students' mindful attention to decompose the nature of given problems and rearrange it to determine ways to solve goal-free requests. Content engagement focuses on learners' involvement with the content-related gameplay, whereas cognitive engagement describes learners' domain-generic thinking to explore problem solutions.

Although GBL researchers have largely investigated wide-ranging natures of learning engagement (Sharek & Wiebe, 2014), prior research has insufficiently explored the ways to maintain high learning engagement. Due to dynamic and contextual traits of learning engagement (Arnone, Small, Chauncey, &

McKenna, 2011), researchers have noticed that learning engagement in GBL may decrease even though a game is likely to draw learners' attention at the beginning of their play. In other words, learning engagement in students' early gameplay can be high due to its novelty effect, and it remains unclear whether a game may maintain students' learning engagement during their entire gameplay. According to Ke's (2008) qualitative analysis, students were likely to lose their attention when they became accustomed to given sensory stimuli in their gameplay (e.g., visual stimuli and interactive functions). Romero, Usart, Ott, Earp, and de Freitas (2012) also agreed with this that decreasing engagement pattern was caused by students' off-task thoughts and actions in GBL. These consistent study findings refer to the importance of designing game actions that fully promote learning engagement in GBL.

Game Design to Increase Learning Engagement in GBL

Because learning engagement is believed to predict students' future learning outcomes (Abdul Jabbar & Felicia, 2015; Eseryel et al., 2014), GBL researchers have proposed specific game design elements to enhance students' learning engagement. Specifically, aligned with evidence-centered design (Shute, 2011), researchers have taken into consideration analyzing students' in-game actions, with an aim to designing game actions that enhance learning engagement purposefully. Plass et al. (2015) highlight the importance of associating students' in-game experiences with learning engagement through game action design. As an example, their study introduced the game *Noobs vs. Leets*, which is a geometry game that asked students to identify missing angles by using their knowledge of multiple angle types. In the meantime, learners in this game are requested to unlock angles to create a path, thus allowing the players to save trapped friends at the cage. The game mechanic of this study made students engaged in game action-based content engagement.

Recent GBL reviews discussed how GBL design should consider key factors that will promote students' learning engagement (Proulx, Romero, & Arnab, 2017; Przybylski et al., 2010). Abdul Jabbar and Felicia (2015) scrutinized major gaming elements that help learners to attain high learning engagement. The study sampled 91 key articles and clustered core game-design features, such as (a) playfulness and discoveries, (b) challenges and conflict, (c) control and choices for attention, (d) scaffolding helps, and (e) learning tools and gaming aids. This study stated that giving students opportunities to discover and test interactive visual stimuli in their game environment may enhance the students' learning engagement. In addition to the visual stimuli, using a variety of game support tools inherent to GBL is believed to facilitate students' proactive game actions in experiencing meaningful learning.

Although researchers have explored the ways a variety of game mechanics are likely to stimulate students' learning engagement, the systematic association analyses between game mechanics and learning engagement are still lacking. It is believed that students' in-game actions can give clues of how game mechanics promote learning engagement, yet there were few explorations in prior GBL design research. Under the evidence-centered design framework (Mislevy, Almond, & Lukas, 2003; Mislevy & Haertel, 2006), recent GBL research has decided to trace how students' learning trajectories are associated with their learning engagement. This data-driven approach in GBL studies has offered researchers opportunities to identify empirical evidence governing how GBL design should foster students' learning engagement.

Data Analysis Approaches to Capture Students' Learning Engagement

Although numerous GBL studies have highlighted the significance of students' learning engagement (Abdul Jabbar & Felicia, 2015; Barzilai & Blau, 2014; Gil-Doménech & Berbegal-Mirabent, 2017; Hsieh, Yi-Chun, & Hou, 2015), the methods to capture their learning engagement are lacking. Although research stated that learners' emotion or motivation states attribute to the level of learning engagement over time, researchers had failed to address the dynamic changes inherent in learning engagement. In other words, even if learners' engagement is deemed a "continuum with different degrees" (Romero, 2012, p. 16), prior studies have largely relied on post hoc test findings via survey instruments. Recent studies stated that those post hoc analysis approaches had scarcely investigated specific game design features that promote students' learning engagement over time. Responding to this problem, researchers have suggested using alternative data analysis techniques that may precisely explore associations between a wide spectrum of game mechanics and students' learning engagement portrayed in their game actions.

In order to capture students' learning engagement, recent GBL studies have increasingly adopted behavior analysis frameworks to examine the type and frequency of students' game actions associated with learning engagement. From early theorems of behavior analyses, researchers argued that a set of behaviors is the result of the "dynamic interplay between an individual and the environment" (Hintze, Volpe, & Shapiro, 2002, p. 994). Sharek and Wiebe (2014) employed a systematic behavior coding that calculated the number of students' game-clock clicks and the time duration they spent on their game-task completions. Although this study did not implement association analyses to identify the relationship between game mechanics and learning engagement, it attempted to use behavioral analyses to quantify students' learning engagement when performing various gameplay actions. Furthermore, Ocumpaugh, Baker, and Rodrigo (2015) introduced a behavior-analysis protocol, demonstrating the ways to quantify students' occurrences of behaviors and affective states. This behavior analysis protocol was employed by several empirical studies to investigate associations between students' learning engagement and interactive stimuli in GBL environments. However, while those studies proposed systematic behavior analytics to capture students' learning engagement states, they still lack empirical approaches to map out statistical associations between game mechanics and students' learning engagement.

When it comes to a data analysis technique in capturing learning engagement, researchers have employed a variety of sequential data mining approaches. Sequential data mining is a kind of learning analytics, which aims to compile salient sequence patterns of students' action occurrences. Associated with GBL research, this analysis technique emphasizes grasping sequences of students' in-game actions and the embedded game mechanics. When used with behavior analysis, sequential data mining has proved effective in indicating potential impacts of game mechanics on students' learning actions during their gameplay. Another goal of sequential data mining is to identify students' in-game actions that promote meaningful learning. Several GBL studies discussed the usage of sequential data mining to study students' in-game behavior patterns (Hou, 2015; Kang, Liu, & Qu, 2017; Yang, Chen, & Hwang, 2015). Kang et al. (2017) used cSPADE pattern mining techniques to analyze learners' logs in the game *Alien Rescue*. They sampled 202 middle school students and decomposed each learner's gameplay patterns according to the number of times she or he used in-game tools. Primarily, they emphasized capturing prominent in-game events, such as which game sequences were used frequently during the students' gameplay. In addition, the study examined the ways in which the students' sequences differed according to their performance level. Furthermore, under the systematic behavioral coding, Hou (2015) implemented sequential analyses of students' in-game actions in two different groups categorized by additional cluster analysis. The study collected learners' in-game action patterns in a roleplaying simulation game for science education. This study analyzed 86 undergraduates' videotaped gameplay sessions to elucidate how students' learning processes changed over time. Specifically, the study found that the different patterns of gameplay predicted degrees of mindful reflection of students about game tasks for learning. The study finding also demonstrated that students' learning engagement during gameplay tends to vary according to their preexisting knowledge as well as their motivation level.

Method

Participants

This study sampled a total of 92 gameplay sessions played by 25 middle school students (males = 15, females = 10) from the sixth to eighth grades in a public school in the Southern United States, with screen- and webcam capture software. We conducted the gameplay sessions in multiple sessions of their math class for 6 weeks. The students of the gameplay sessions were randomly seated and played at their own pace. The number of gameplay sessions sampled for each student ranged from 1 to 8 (mean = 5.15, $SD = 1.71$). We sampled a different number of gameplay sessions across students to better capture a variety of game tasks and hence actions engaged by the students, and students differed in the game tasks completed. A teacher and multiple facilitators gave technical help when the students needed. A gameplay session for each individual lasted around 50 minutes on average. At the beginning of the gameplay session, all students watched a 15-minute video tutorial that described how to use basic game mechanics to fulfill given game tasks.

Game: E-Rebuild

E-Rebuild is a 3D architecture game that offers a single-player mode that allows gameplayers to engage in architectural design to rebuild a disaster-destroyed structure or neighborhood for refugees. This game is designed to increase learners' engagement and performance in math problem-solving through fulfilling various architectural design tasks. The targeted content knowledge in this game complies with the mathematics Common Core State Standards. The students in this study performed three major tasks during the gameplay: (a) material trading, (b) structure (e.g., shelter) building, and (c) allocation of refugees in the shelter (Ke, Shute, Clark, & Erlebacher, 2019). In addition to the three major game tasks, the game episodes in this study depicted the scenes of (a) island, (b) desert, and (c) urban school (Figure 1). While the students assign refugees to shelters in all three episodes, they must alter their building techniques because of variant design needs and limited resources in the game world.

Concerning material trading, in all three game episodes, the students must visit the store to buy an appropriate number of building materials, such as containers, bricks, and flooring. The amount of materials purchased should be sufficient to construct shelters that will accommodate all the refugees' living space needs (which involve the comprehension and application of the concepts of area, unit, and ratio). In addition, the students need to calculate the cost of all the materials, by considering the discount offers that embed the concept of *percent*. The player should estimate a trading strategy to determine whether she or he can spend less money on the resources. The less money the students spend on their resources, the better scores they can achieve in the game.

When constructing shelters in different episodes, students need to engage in different building acts. For example, in the island episode, the students are prompted to buy a minimum number of shipping containers to compose a preset structure based on 2D and 3D visual aids. In the desert episode, the students build an adobe-style red brick house. They must estimate/purchase the number of bricks needed and stack/join them to construct the house. This task requires learners to exhibit more dexterity in executing a series of building

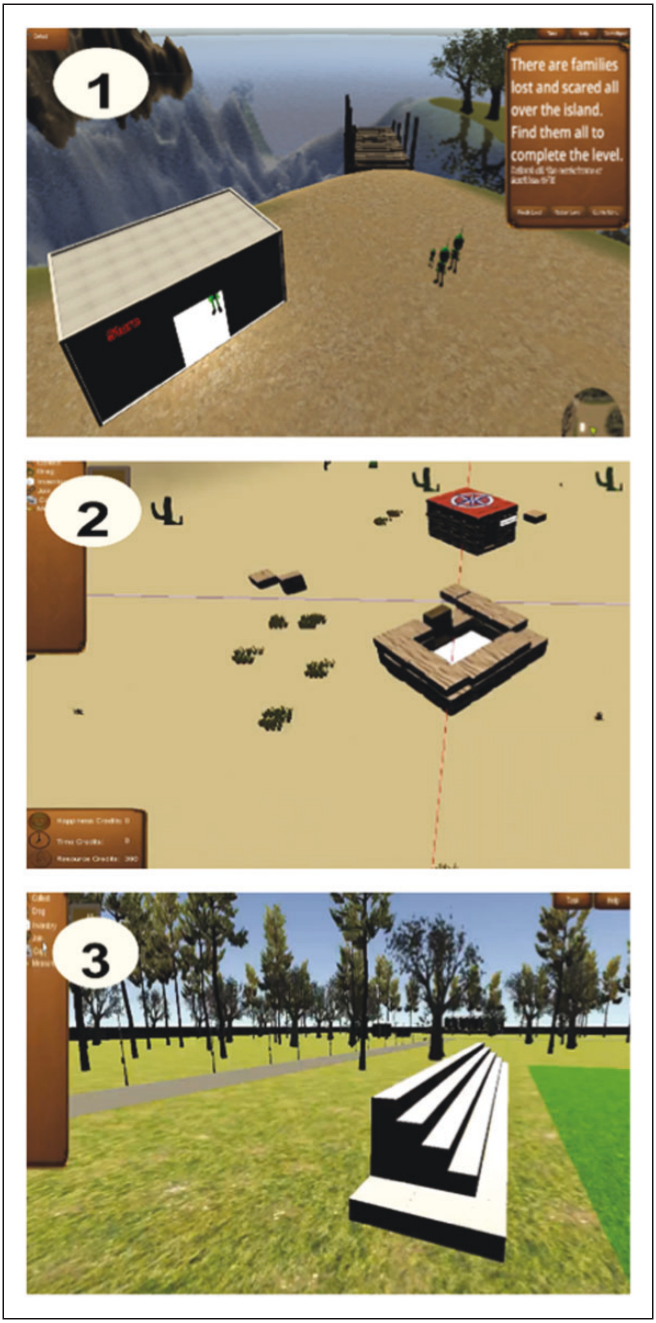

Figure 1. Three screen-captured images demonstrate major gameplay scenes in each episode of the game E-Rebuild (1 = shipping container, 2 = desert, and 3 = school).

acts (e.g., object positioning, rotation, stacking, joining, and pasting) embedded in the game. In the urban school episode, the students must build variant facilities with both containers and bricks to restore a school campus and must do so without any visual aids. Rather, the students need to investigate the design features of the existing facilities in the school and create new buildings correspondingly. Regardless of the types of game episodes, the students must apportion refugees to a given number of shelters by addressing variant living space needs.

Data Preprocessing

We conducted in-depth analyses with behavioral observations based on a predefined ethogram. An ethogram defined a series of salient behaviors with a classification of the elements and function of each behavior. Via an initial open-ended coding with the gameplay behaviors, we developed a coding scheme for the later systematic behavior analyses via the analytic tool *BORIS* (Friard & Gamba, 2016). *BORIS* is an open-source software designed specifically for in-depth behavior analyses. Based on the coding scheme, the software allows the researcher to label types of students' behaviors and review relevant sample materials simultaneously. Along with the screen-captured gameplay behaviors, the video samples also captured students' upper bodies and facial expressions during gameplay.

Multiple expert E-Rebuild game players who also have expertise in GBL research participated in developing an initial ethogram of the study. To begin, in open coding, they spent 3 weeks working to implement exploratory behavior analyses and create an initial coding scheme. They then performed the iterative steps to elaborate the coding scheme. This coding scheme used two types of behavioral codes, point and state behaviors. While a point code counts the number of behaviors, a state code estimates a particular behavior's duration. All behavior codes for the analyses are shown in Table 1.

As shown in Table 1, the independent variables in this study were all the game events (i.e., Building and UsingHelp) in which the learners engaged, while the dependent variable is two states of learning engagement (i.e., cognitive and content engagement). Cognitive engagement represents a learning state in which students attempt to perform multifaceted steps to complete a game goal, whereas content engagement refers to behavioral moments interacting with the GBL content. For example, a student was requested to place a few shipping containers in the ground. At the beginning of his building process, he appeared to be fully aware of how he would locate each container based on a given visual blueprint. The student leaned his upper body toward the computer screen and looked engaged and effortful pondering on the ways to move the containers appropriately. These observations suggested the state of cognitive engagement. As another example, when the student hovered their mouse

Table 1. Behavior Codes in the Coding Scheme.

Major behavior codes	Definition	Modifiers
Cognitive engagement	Learning engagement that focuses on students' strategic approaches in problem-solving tasks in a game	Mining information, planning, evaluating, testing, and refining
Content engagement	Learning engagement that focuses students' attention on content knowledge comprehension	Processing, application, calculation
Building	All the actions needed to complete building construction tasks	Copy, joint, position, stacking, rotating, recollecting, undesirable perspective
Site-surveying	Measuring tool to estimate numerical value of construction sites	Intended/unintended
Trading	All the actions of buying materials for building design tasks	Accurate/inaccurate
Allocation	All the actions to assign each refugee to the shelter	Appropriate/inappropriate
UsingHelp	Processing in-game scaffolds	Help panel, summary screen, scratch tool tips

cursor over the item inventory and read the information of each item, the coders labeled the behavior as mining information (or a subcategory of cognitive engagement). In another case, players were observed calculating the total cost of the game resources (e.g., red blocks, a door, and a floor) based on the provided price information. Such a behavior was coded as content engagement as well.

Data Analysis

Sequential analysis. This study extracted several types of sequential analysis measures from the systematic human behavior observations (Quera & Bakeman, 2000; Suen & Ary, 1989). They were overall behavior frequencies, a transition probability matrix, and a random permutation test. Overall behavior frequencies demonstrate students' behavior tendencies, indicating how often students attempted to use certain in-game action. This result helps to understand the proportion of each in-game behavior type students used. A transition probability matrix (Friard & Gamba, 2016) is a stochastic matrix derived from a hidden Markov chain algorithm (Ghahramani & Jordan, 1997). Compared to existing sequential analysis techniques, the hidden Markov chain can detect a causal relation between game event variables and the dependent variable (i.e., learning engagement). This measure predicts the likelihood of after behavior through collecting a series of behavior events. In this study, all the sequentially arranged behavior codes in each row have a unique numeric probability value associated with the behavior codes in each column, respectively. The value in each cell of the matrix represents the association between two events. Thus, each dyadic association value in the matrix denotes the degree to which a certain behavior is likely to promote another behavior. Based on this rule of a transitional probability matrix, this study sampled only those behaviors that were likely to promote each type of learning engagement. We converted all raw behavior analysis data to the form of a transition probability matrix. This study initially captured all 1,490,020 association cases from the 92 behavior-annotated video files in the transition probability matrix. To compute significant associations among numerous cases, this study implemented a set of data cleaning procedures in advance—specifically, we filtered in only the behaviors that are most likely to promote learning engagement (i.e., content and cognitive engagement) and tagged as mostly probable paths (or having the highest probabilities). In the analysis, we set the cutoff value 0.10 as significant. Once the path was below the threshold value, it was tagged as a rare transition.

We also employed a random permutation test for analyzing whether certain in-game actions by students are likely to occur with statistically high chances (Bakeman, Mcarthur, & Quera, 1996). The random permutation test is a non-parametric analysis that does not assume the normal sample distribution. Sequential analysis studies are largely exposed to the problem of skewed marginal distributions. Alternate to the lag-sequential analysis as parametric statistics, a random permutation test is designed to detect whether the relation between two behaviors is empirically meaningful or occurs by chance. While the transition probability matrix emphasizes the likelihood of behavior occurrences regardless of the numbers or lengths of sequences, the random permutation test aims at examining whether students' in-game actions are statistically meaningful among the behavior association cases from the transition probability matrix.

Thematic analysis. To further explore how students' specific in-game actions were associated with high learning engagement, a qualitative thematic analysis was also performed (Braun & Clarke, 2006; Braun, Clarke, Hayfield, & Terry, 2019). The thematic analysis was implemented to depict the contextual factors largely associated with students' behavior patterns that promote GBL engagement. The analysis helped to explain how and why students' gameplay sequences occurred in a certain way. Multiple behavior coders initially piloted themes from the observations and then finalized said themes through iterative elaborations. We triangulated the findings of sequential analysis and thematic analysis to synthesize the pattern of students' in-game actions in relation to learning engagement.

Results

Sequential Analysis

Descriptive statistics. Using systematic behavior observations, this study initially sampled a total of 9,021 behavior events from the participants' gameplay sessions. We found a total of 505 behavior combination cases. The bar and pie charts that show the proportion and numbers of key behavior events from the observation coding are shown in Figure 2. The most frequent behavior type is building ($n = 4{,}749$). In addition, there are frequent events of Learning Engagement ($n = 2{,}657$), UsingHelp ($n = 1{,}041$), Allocation ($n = 288$), Trading ($n = 190$), and Site-Surveying ($n = 96$). There are a total of 613 behaviors (23%) with content engagement, whereas the number of behaviors under cognitive engagement is 2,044 (77%).

Exploratory transition probability matrix analysis. By analyzing the transition probability matrix, this study confirmed several causal relations among the game actions and learning engagement. As illustrated in Figure 3, a total of 12 significant relationships (Pr > .10) was captured. With respect to content engagement alone, there were four major causal relations among game events and each type of content engagement (Appropriate + Allocation → ContentEngagement + Application, Accurate + Trading → ContentEngagement + Application, Accurate + Trading → ContentEngagement + Processing, and ContentEngagement + Calculation → Content Engagement + Processing). According to the order of the relations between the game behaviors and engagement, the one action most likely to promote the state of content engagement was *appropriate allocation*, in which the learners assigned families to each shelter appropriately during the gameplay (Pr = .40). Furthermore, trading building materials in the store during gameplay was found as a behavior that promotes the knowledge "application" state of content engagement (Pr = .33) and was confirmed to be an event that predicts the "processing" state of content engagement as well (Pr = .28). Finally, the "calculation" state was positively associated with the "processing" state in content engagement (Pr = .21).

Five casual relations were identified in cognitive engagement overall (Intended + Building + Positioning → CognitiveEngagement + Testing&Refining, UsingHelp → CognitiveEngagement + MiningInformation, UsingHelp → CognitiveEngagement + Planning, SiteSurveying → CognitiveEngagement + Planning, and Intended + Building + Stacking → CognitiveEngagement + Testing&Refining). According to the results, the game actions of object positioning (Pr = .47) and stacking (Pr = .13) during gameplay promoted the testing and refining states of cognitive engagement. Furthermore, UsingHelp, such as interacting with the help panel in the game, also predicted learners' acts of mining information (Pr = .36) and planning (Pr = .18) in cognitive engagement. Learners' site-surveying actions, such as measuring the

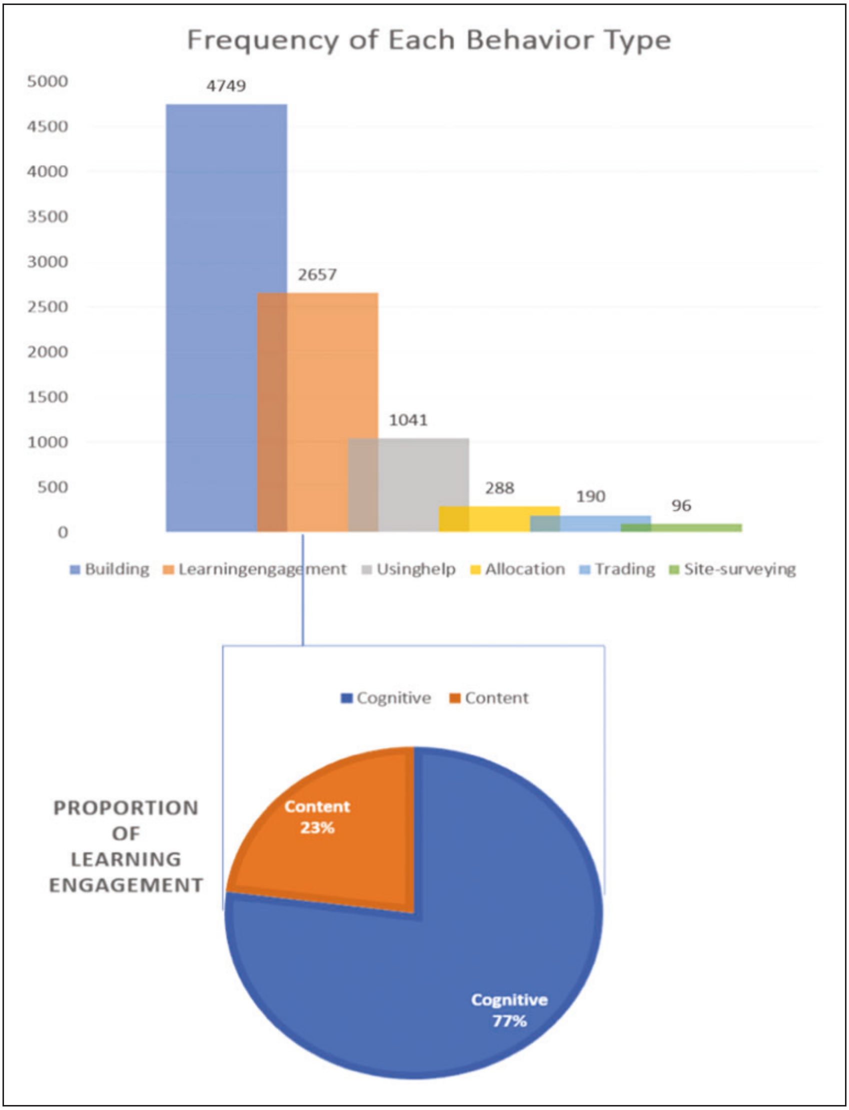

Figure 2. Frequency of each behavior type.

distance and size of the containers or blocks during gameplay, also promoted planning behavior (Pr = .18) in cognitive engagement.

Notably, content engagement also predicted cognitive engagements significantly (ContentEngagement + Calculation → CognitiveEngagement + MiningInformation and ContentEngagement + Processing →

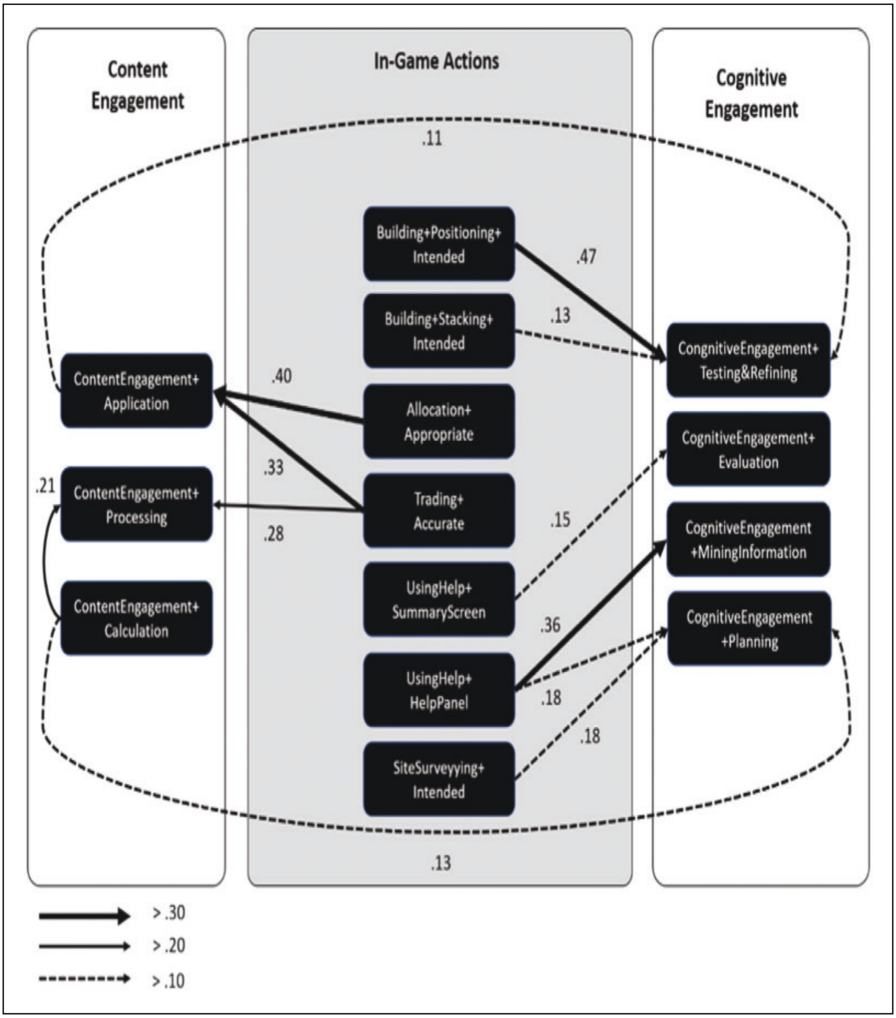

Figure 3. Probability values and directions among students' in-game actions.

CognitiveEngagement + MiningInformation). Calculation (Pr = .13) and processing behaviors (Pr = .11) both promoted information mining in cognitive engagement.

Random permutation test. This study implemented a random permutation test to analyze the statistical significance of the game sequences with high likelihood from the transition probability matrix analysis. The permutation test was designed to approximate the p value of each behavior path by simulation.

Table 2. Summary Results of the Random Permutation Test.

Behavior sequences	p value (permutation)	Null hypothesis
Appropriate + Allocation → ContentEngagement + Application	.03	Rejected
Accurate + Trading → ContentEngagement + Application	<.01	Rejected
Accurate + Trading → ContentEngagement + Processing	<.01	Rejected
ContentEngagement + Calculation → Content Engagement + Processing	<.01	Rejected
Intended + Building + Positioning → CognitiveEngagement + Test&Refining	<.01	Rejected
UsingHelp → CognitiveEngagement + MiningInformation, UsingHelp → CognitiveEngagement + Planning	<.01	Rejected
SiteSurveying → CognitiveEngagement + Planning	<.01	Rejected
Intended + Building + Stacking → CognitiveEngagement + Test&Refining	<.01	Rejected
ContentEngagement + Calculation → CognitiveEngagement + MiningInformation	<.01	Rejected
ContentEngagement + Processing → CognitiveEngagement + MiningInformation	.02	Rejected

To assess a significance threshold of behavior sequences, this study conducted 1,000 permutations under α-level of .05 (Studer, Ritschard, Gabadinho, & Müller, 2011). For i number of permutation test, the order of the captured behavior sequences was randomly shuffled. The null hypothesis of this testing was that behavior sequences occurred only by chances. As shown in Table 2, the null hypothesis was rejected for all sampled sequences from the transition probability matrix, indicating that all the behavior sequences were statistically significant.

Qualitative Results

Enactments of students' content engagement by material-trading and refugee-allocation actions. Students' gameplay actions, especially material-trading and refugee-allocation, facilitated students' math computation behaviors. In a material-trading action, players had to calculate the cost of an item, gauge the discount offer for a batch purchase, and plan the purchasing strategy to reduce the cost. In a refugee-allocation action, the students had to translate the ratio and unit statements specifying different refugees' living space need, calculate the total and unit spaces available and needed, and coordinate all these different pieces of information to configure the appropriate number and type of refugees to be assigned to each shelter.

As observed, the participant *Christina* tended to physically count on her fingers to tally the total number of containers or blocks during her gameplay. Although her overall game performance was not comparable with other students, she appeared enthusiastic in performing her math computation tasks. In addition, she also tended to zoom in on her game screen to focus on each price of the products offered by the item shop. She occasionally hovered her mouse cursor to double-check the price of each item to ensure her computations. These in-game actions demonstrated her deliberation on accurate math computations when performing material trading actions. After multiple material trading transactions, she became accustomed to the item cost calculation process. She also realized that she could buy building items by batch at a reduced price. Her subsequent trading actions were obviously faster than her previous attempts.

Regarding the refugee-allocation action, the player is supposed to collect and integrate all related background information, such as the size of each structure or shelter, unit space need of each type of refugee, as well as the number and composition of refugees. At an initial attempt, participant *Shaydin* tended to assign refugees to each house randomly without computing the space needed for refugees in relation to the space limit of each shelter. He iteratively failed at this action, without understanding the reasons. *Shaydin*'s multiple failures made him reflective and ultimately noticed that he needed to first examine the space needs of each type of refugees. He started to process all related and embedded math concepts effortfully since then. *Shaydin* appeared to be engaged in his computation during his allocation of the refugees. After he finally succeeded in the refugee allocation action, he exclaimed, “I saved this family!”

Enactment of students’ cognitive engagement by a series of building actions. Some students in the gameplay were inclined to become cognitively engaged when implementing a set of building sequences in response to their design quests. As designed, once students complete their material-trading action, they need to assemble the building materials to construct a shelter. They have been trained to plan and execute a series of building acts in an optimal sequence. For example, *Brandon* was a successful performer in building his adobe-style house during the desert episode. During his building action, he often referred to the game task narrative to ensure that his design artifact met the task requirement. His early gameplay experience fostered his dexterity in the building action. He strived for an optimum state in his building work and would iteratively refine his acts, even when the quality of his artifact was sufficient enough to pass the game level. His gameplay behaviors also demonstrated a strategic planning effort. For example, his increased uses of site-surveying tools demonstrated the gradual development of a sensible gameplay style.

Jayden was another mindful player in his building actions. In particular, he was astute with his building actions at the school episode. The goal of this design quest was to build a grandstand for the school stadium. The key challenge of this quest was that the player could only use 20% fewer blocks than those of the blocks they could purchase in constructing the grandstand. Different from other students who experienced game failures without being aware of this design requirement, *Jayden* was attentive. After he failed in his game quest a few times, he began surveying the construction site again and then examined the structure of the existing grandstands. He noticed that the backside of the exemplary grandstands had numerous hollow spaces, which indicated that he could use fewer blocks to simulate/compose the stand. With this insight, he attempted to replicate the design of the example grandstands. Although his replication was not fully successful, his explorations allowed him to change his design plan and modify his building actions. He was also enthusiastic in sharing his design insights with other classmates, who were playing the game concurrently.

Although most students were found engaged in the building actions, quite a few students were inattentive. They had hard time or lack awareness of analyzing the composition of the structure to be built. Even when they read the task panel to search task-relevant cues, they failed to attain insights.

Using in-game help to support task-related math variable interpretation. In-game learning support appeared helpful to foster students' design-based, math problem-solving. At the very beginning of gameplay, most students failed to connect task-relevant, contextual information in the game world with the design problem to be solved. Instead, they would pick a random number of materials and built a random structure. After a few failures in the game tasks, they gradually realized that they need to purchase the proper amounts of blocks and the building has to satisfy certain design conditions. Their behavior pattern indicated that they attempted to hypothesize on the math computations based on environmental variables in the game world. For example, after multiple game failures, students tended to execute site-surveying actions before they purchased their materials. They were much more frequent in using the task/help panel to attain the salient task information. In other words, the students were attentive in processing environmental variables of their game quest. Also, the embedded in-game learning supports (e.g., help panel, game summary screen) had facilitated the students' comprehension and coordination of the embedded math variables in the game world to solve design-based math context problem.

Discussion

Enhanced Learning Engagement Elicited by Students' In-Game Actions

The present study explored the association between students' in-game actions and learning engagement during their math gameplay. According to prior study findings (Abdul Jabbar & Felicia, 2015; Przybylski et al., 2010), students' mastery of game mechanics and learning support uses were potentially effective in enhancing their learning engagement. The current behavior observations of students' gameplay supported this finding. This study demonstrated how students become engaged in learning via salient game actions.

Specifically, we found that refugee allocation and material trading actions promoted students' content learning engagement. Using in-game building design tools with embedded learning support enhanced their cognitive engagement. This study finding suggests that game designers should examine the nature of different game actions in relation to students' content and cognitive engagement.

A series of building design sequences that students experienced served as the introduction to their problem-solving tasks, which contributed to their development of gameplay *heuristics* (Schoenfeld, 2014), which could mediate the students' enhanced cognitive engagement. This study found that the students were inclined to use in-game learning support in their building actions. The in-game learning support motivated and helped the students to refer to given contextual clues from each game episode. During their iterative building actions, students become cognitively engaged because their recursive in-game actions possibly developed their competency in game control (Przybylski et al., 2010; Schoenfeld, 2014).

Students' In-Game Actions and Mathematical Thinking

The qualitative findings of this study support that students' in-game actions enabled the enactment of mathematical thinking. Specifically, in-game actions of materials trading and refugee allocation have activated students' identification and interpretation of mathematical information distributed across game objects (e.g., translating the ratio and unit statements, checking the price and geometric properties of building items) and the application of the conceptual understanding to solve a mathematical problem (e.g., computing the individual and total space need in relation to the space limit to allocate refugees). They demonstrated mindfulness in collecting and translating task-related mathematical information and applied math-related problem-solving procedures. In addition, students have demonstrated cognitive engagement in terms of strategic planning, purposeful construction site survey, and geometric shape analysis during building actions. Based on prior research on learning transfer (Boaler, 1993; Bransford & Schwartz, 1999), the more variations students experienced in gameplay-based mathematical practices, the greater transfer they would achieve in developing and applying mathematical thinking. In this study, the students engaged in content-related game actions (e.g., trading and allocation) in different game tasks and construction scenarios (e.g., in the scenes of an island, a desert, and an urban school). They hence performed their mathematical thinking iteratively through in-game actions tailored to various in-game circumstances.

Video Analysis-Based Data Capturing on Learning Engagement in GBL Research

Prior GBL research relatively lacked the measurement that captures students' dynamics change in GBL engagement. Compared to prior works in GBL (Gil-Doménech & Berbegal-Mirabent, 2017; Jagušt, Botički, & So, 2018) and on using video analysis for in-depth observations of students (Derry et al., 2010; Goldman, Pea, Barron, & Derry, 2007), this study adopted a synthesized data-capturing approach including both sequential analysis and thematic analysis. This analysis approach helped to elucidate interplays occurred between students and in-game tools. The study finding evidenced that game actions are salient indicators showing when and how students become engaged as related to their gradual developments of mathematical thinking. This study illustrated that students' meaningful gameplay actions correspond with their mathematical sense-making steps. The results of this study would inform future research on predicting students' learning engagement to support adaptive learning in GBL for math.

Conclusion

Overall, this study found that students' in-game actions significantly predicted their learning engagement in their math gameplay. The findings of the sequential analysis and thematic analysis coherently indicated that variant types of students' in-game actions fostered learning engagement differently. This study also found that the in-game learning support enhanced students' understandings of in-game math variables and actions.

Limitation and Future Research

This mixed-method study investigated the association between students' in-game behaviors and their learning engagement with a relatively small sample of students. To corroborate the study findings, a future experimental study should be conducted. Future research should also investigate how the in-game learning support promotes students' in-game actions with high learning engagement. Moreover, future studies can also examine how students' enhanced learning engagement mediates their mathematical problem-solving in GBL.

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