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Using gameplay data to examine learning behavior patterns in a serious game

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ABSTRACT

Research has shown how open-ended serious games can facilitate students' development of specific skills and improve learning performance through problem-solving. However, understanding how students learn these complex skills in a game environment is a challenge, as much research uses typical paper-and-pencil assessments and self-reported surveys or other traditional observational and quantitative methods. The purpose of this study is to identify students' learning behavior patterns of problem-solving and explore behavior patterns of different performing groups within an open-ended serious game called *Alien Rescue*. To accomplish this purpose, this study intends to use gameplay data by incorporating sequential pattern mining and statistical analysis. The findings of this study confirmed the results from previous research (using *ex situ* data such as interviews) and at the same time provide an analytical approach to understand in-depth students' sequential behavior patterns using *in situ* gameplay data. This study examined the frequent sequential patterns between low- and high-performing students and showed that problem-solving strategies were different between these two performing groups. By using this integrated analytical method, we can gain a better understanding of the learning pathway of students' performance and problem-solving strategies of students with different learning characteristics in a serious games context.

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1. Introduction

1.1. Serious games analytics

Serious games (SGs) are one type of learning environments. SGs are designed to train specific skills and improve learning performance through real-world problem-solving. Their essential attributes are clear goals, challenges that motivate students to complete a task, and tasks through which students develop mastery (Foundation of American Scientists, 2006; Loh, Sheng, & Ifenthaler, 2015). Research on SGs has centered on the positive impact on student engagement or the effectiveness of combining data obtained from both traditional methodologies such as experimental design and traditional achievement tests or self-reported surveys (Barab et al., 2009; Liu, Horton, Kang, Kimmons, & Lee, 2013; Liu, Horton, Olmanson, & Toprac, 2011). Recently, however, scholars have raised several concerns. Student skill-building within SG environments is difficult to assess via traditional educational measurements such as achievement tests. Although complex games like SGs with multiple solution paths alongside complex functions—the so-called open-ended serious games first identified by Squire (2008)—allow students to take diverse paths when solving a problem, students' learning processes remain to be a challenge to identify. Therefore, SG researchers have paid more attention toward finding ways to track students' learning processes and to assess their learning performance from this tracking information. The emergence of serious games analytics has enabled researchers to investigate students' in-game behaviors (Loh, 2012; Wallner & Kriglstein, 2013). Serious games analytics refers to analytics or insights converted from gameplay data within a SG for the purpose of performance measurement, assessment, or improvement (Loh et al., 2015). In SG environments, students' actions and behaviors are traced *in situ* through numerical variables, which are referred to as *in situ* data. This data differs from *ex situ* data such as self-reported survey data (pretest and posttest) collected outside the game system. Particularly, the sequence of actions taken by

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students during the process of problem-solving within a SG is considered evidence of the users' learning performance (Loh & Sheng, 2014; Schmidt & Lee, 2011).

One benefit of user-generated SG data is its spatial-temporal nature (Loh & Sheng, 2015). For example, game designers can understand user behaviors (e.g., any unexpected behaviors) by tracing the exact locations of users for a specific time frame to improve the game design. One approach to identify behavior patterns employed by groups of learners within a game environment is sequential pattern mining which was first introduced to identify customer purchase sequences from a large database of customer transactions (Agrawal & Srikant, 1995; Zaki, 2001). This analysis identified frequent subsequences under the condition that the occurrence of the subsequences must exceed a certain user-specified minimum support. The minimum support for a sequential pattern in their study indicates the percentage of total customers who support the pattern. Zhou, Xu, Nesbit, and Winne (2010) noted several challenges of sequential pattern analysis; for instance, not all actions recorded in a log file are associated with what the researchers intend to examine. Specifically, a system within a learning environment can generate multiple log events of a learner's movement including all mouse clicks whether they are relevant to the study or resulting from unskilled mouse control. Therefore, it is necessary to translate low-level raw logs to higher-level meaningful actions through the data preprocessing process. One challenge of these spatial-temporal data analyses is the inability of analyzing the timing of events; that is, it analyzes only sequences of events (Clark, Martinez-Garza, Biswas, Luecht, & Sengupta, 2012). Within the sequences, there is no information such as when the sequences of events actually happened. Therefore, it is essential to seek for a proper approach that can handle any important factor of researchers' concerns such as the timing consideration (Clark et al., 2012).

Different data mining methods (e.g., Bayesian networks, k-means cluster analysis, sequential pattern mining) have been applied to serious games analytics. However, these methods have critical limitations in educational contexts, in which the methods must be directed by theoretical principles about complex learning (e.g., problem-solving and scientific inquiry) (Clark et al., 2012; Zhou et al., 2010). Further, insufficient empirical studies address how these data mining techniques can inform pedagogy and assessment of inquiry specifically in open-ended serious game environments. Despite the potential benefits of using serious games analytics for learning assessment, scant research provides evidence of the relationship between students' learning behaviors and their academic performance in SG environments. Therefore, it is vital to investigate learning behaviors that can provide insights into understanding students' learning performance in SGs. This effort would facilitate learning processes and strategies across student populations that include novice-to-expert or low-to-high performance levels.

1.2. Problem-solving processes of learners with different levels of performance

Literature has shown expertise often influences the process of problem-solving (Jonassen, 2000; van Merriënboer, 2013). To examine the influence of expertise, researchers have considered differences in the level of expertise. For example, Wiley (1998) noted that the extent an individual learner possesses domain knowledge is a central component of expertise. Researchers have proposed the essential components of becoming an ideal problem solver; that is, a learner who possesses a high level of expertise. Gick (1986) proposed a model of the problem-solving process which included: (1) representing a problem, (2) searching for solutions, (3) implementing the solutions, and (4) achieving success or iterating through the previous steps again. Gick's model assumes that once learners identify an existing solution scheme to solve a problem (i.e. they have previously solved a similar problem), they will be able to avoid a searching step and instead take a shortcut. Therefore, when learners have a high level of expertise (i.e. an ideal problem solver), they can be more efficient or productive.

There are differences between experts and novices to the extent to which an individual possesses domain-specific knowledge and how to structure that knowledge (Dreyfus, 2004; Dreyfus & Dreyfus, 2005; Jonassen, 2000; van Merriënboer, 2013; Wiley, 1998). In a study by Chi, Feltovich, and Glaser (1981), students were asked to organize physics problems in their textbook in any ways they wanted. Novices tended to approach the main problem—the organizational task—based on the surface structures of the problems, while experts organized the problems based on physics principles to solve the main problem (Chi et al., 1981). According to Chi et al. (1981), problem-solving strategies were differently used between novices and experts within given scientific problems, especially in terms of a means-ends-analysis. Novices tended to work backward deciding a goal of the problem and then a formula they needed. In contrast, experts often worked forward proceeding toward sub-goals and applying the information they found during each procedure to solve the problem. When learners confronted the challenges of uncertainty, novices often gave up solving the problem or solved the problem based on their existing knowledge, while experts tended to use given information to work forward. Such findings suggest that expertise influences a student's problem-solving processes and strategies. It is essential to examine how students with different expertise solve a problem differently in various contexts such as different school subjects or different learning environments.

Although previous studies have evaluated students' learning process on educational games or simulations (Barab et al., 2009; Liu & Bera, 2005; Liu et al., 2009; Liu, Cheng, & Huang, 2011), scanty empirical research exists on in-depth analyses of behavior patterns. Recently, Hou (2015) examined the latent learning behavior patterns of students with different levels of flow by analyzing the videotaped screen recording. This study applied cluster analysis and sequential analysis (Bakeman & Gottman, 1997) and confirmed the use of behavior pattern analysis as a potential method of identifying a variety of learning behavior patterns within a role-playing simulation game in science education. Such findings suggest that an analytical method such as behavior pattern analysis can provide a detailed examination of learning processes in problem-solving. However, typical achievement tests and data mining techniques not directed by theoretical principles about complex learning skills often fail to wholly account for how students learn complex skills through solving scientific problems within a game context. Given these challenges, this research intends to use *in situ* gameplay data (captured as a student interacts with various tools embedded in a game environment) to investigate students' learning processes. This study expands on previous research on students' cognitive process patterns in *Alien Rescue* by incorporating the combination of statistical analysis with data mining in an investigation of learning patterns among students with different expertise. The following research questions guided this study:

1. What patterns emerge as students interact with various in-game tools?
2. How do different levels of performance impact student learning pathways?

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