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

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A B S T R A C T

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.

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?

2. Method

2.1. Participants

Participants included a convenience sample of 202 sixth graders from a middle school in the Southwestern area of the United States. The school used *Alien Rescue*, designed for 15 50-mins class sessions, as part of their sixth-grade science curriculum. The participants in this study used *Alien Rescue* for thirteen days, given their school schedule, on an individual computer; however, group work was encouraged.

2.2. Research context

The open-ended serious game, *Alien Rescue* (http://alienrescue.edb.utexas.edu), was developed by a research group consisting of both faculty and graduate students in the Learning Technologies Program at The University of Texas at Austin. Guided by a design-based research framework (Brown, 1992; Cobb, Confrey, diSessa, Lehrer, & Schauble, 2003; Wang & Hannafin, 2005), this group aspired to generate new theories and improve educational practices using iterative design, development, implementation, and analysis within an authentic real-world setting. During the past decade, *Alien Rescue* has been used as part of the science curriculum by over a dozen middle schools in Central Texas, as well as by schools in at least twenty-nine states and four countries.

Alien Rescue integrates multiple attributes of open-ended serious games along with problem-based learning pedagogy, in which students with different expertise (e.g., expert and novice) use various approaches to solving problems (Glaser, 1991). Authenticity is achieved by placing students in the role of young scientists who are asked to join a United Nations rescue operation to save a group of six distressed aliens displaced from a distant galaxy because their home planets have been destroyed. Students are engaged in scientific investigations with a clear goal of finding a suitable home in our solar system to relocate for each alien species. While students find a solution for each species, they are encouraged to repeat tasks in order to build mastery. The central problem of finding the aliens' suitable homes is complex, and students are not provided explicit instructions for problem-solving steps. Since this central problem is ill-structured and there are multiple ways to find suitable homes, students need to justify a solution by providing rationale and evidence. Students need to explore the multiple functional spaces for supporting cognitive processes and hypotheses testing, and develop strategies for utilizing different in-game tools (see Fig. 1). Through this open-ended serious game, students experience cognitive processes akin to real-world scientific inquiry and practice high-level cognitive skills such as hypothesis generation and problem-solving.

2.2.1. In-game tools

To support students' problem-solving processes, *Alien Rescue* provides 10 tools, each of which has been categorized based on Lajoie's four types of cognitive tool functions (1993; see Table 1): (a) share cognitive load, (b) support cognitive and meta cognitive processes, (c) support cognitive activities that would otherwise be out of reach, and (d) support hypothesis generation and testing. Since each alien has unique needs and characteristics, students are challenged to gather information embedded in different tools and integrate this information to solve a complex and ill-structured problem for each alien. Therefore, strategic use of these in-game tools is essential to complete the students' task. Ten tools are accessed through a two-layer interface. The first layer consists of four primary tools found in the space station *Paloma*, including Alien Database, Probe Design Center, Mission Control Center, and Communication Center. The second layer consists of the rest of six tools including Solar System Database, Missions Database, Concepts Database, Spectral Database, Periodic Table, and Notebook, each of which can be overlaid anytime with any tool that students want to access.

2.3. Data sources

2.3.1. Gameplay data

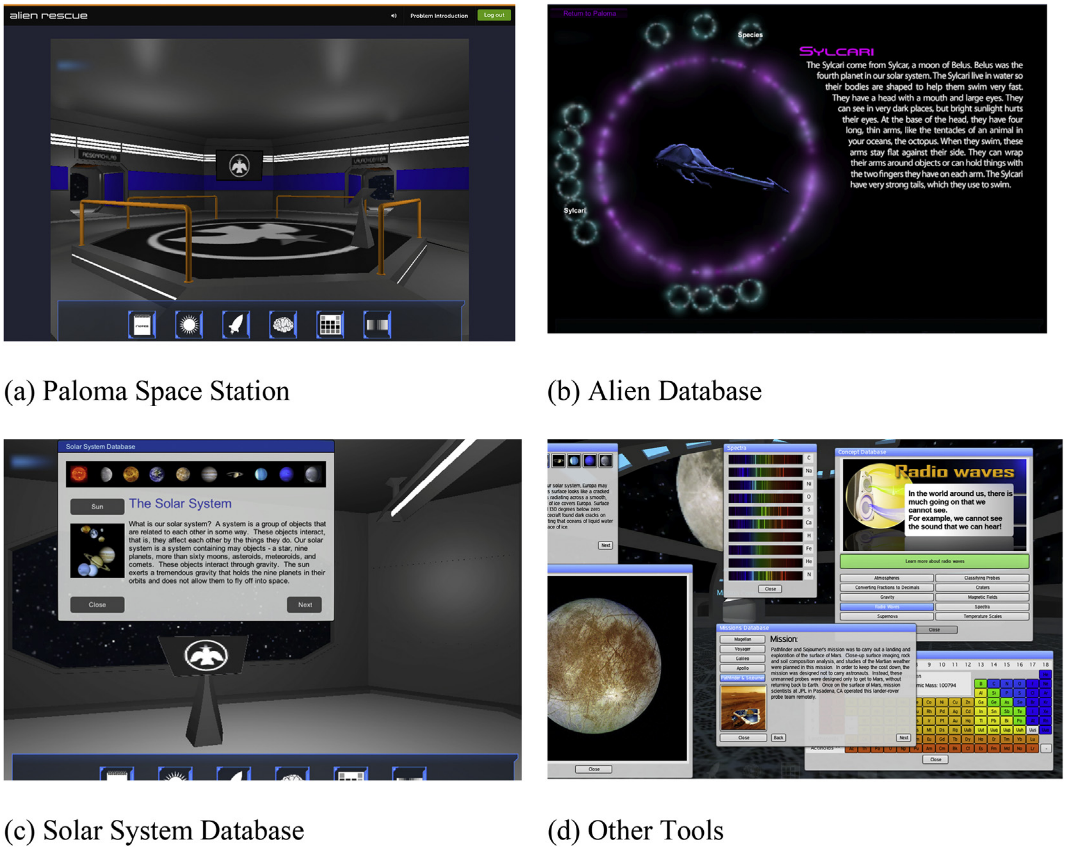
The overall gameplay data—is denoted as Navigation data in this study—were used to identify students' behavior patterns as they engaged with various in-game tools in *Alien Rescue*. The game records every action as each student interacts with the environment. Data contains a student identifier, a tool that a student accesses, a type of action a student is taking (e.g., Open or Close), any additional notes on the student's interactions, and a timestamp for each action (see an example in Table 2).

2.3.2. Problem solutions

Students' solutions were evaluated by how successfully a student solved the central problem. Students use the Message Tool to submit a solution(s) for each alien, and they must indicate an appropriate home for each species and provide a rationale (see Table 3). Students can submit multiple solutions for each alien species, which reveals the results of students' problem-solving processes—that is, rationales of their solutions using the gathered data. In a real classroom environment, students move through the problem-solving processes at their own pace. Therefore, some students are able to submit a solution for each of six alien species while others cannot. In addition, since there are multiple possible answers and multiple suitable homes for each alien, students can submit multiple solutions for each alien species. In this study, all submitted solutions are considered for grading each student's score. For example, a student received 6 points if she submitted a solution for each of six alien species and selected an appropriate home for each alien. If a student selected an appropriate home for each of five aliens and an inappropriate home for one alien, this student received 5 points.

2.4. Data preprocessing

Data cleaning process included only meaningful navigation data. We identified a specific period for each class from the raw navigation data based on the classroom observations. For example, the navigation data that was not recorded during the classroom sessions was removed, this is because some students accessed the game after school, during the holidays, or on school assessment testing days. We used Python to transform the raw navigation data into sequence data to perform sequential pattern mining. Navigation data contains a student identifier, a tool, a type of action, and a timestamp for each action (see Table 2). Each tool generates different actions based on its function; for example, students can zoom in and out of 3D models of each alien species in Alien Database, which is not available in other tools. Therefore, we only included 'Open' action to focus on the sequences of tool use. For instance, the sequence of tool use for the student with 5294 identifier in Table 2 is {Probe Design Center, Probe Design Center, Alien Database}. The navigation data were then translated into two different time sequence formats. One in a vertical format was developed to fit into the sequential pattern mining analysis (see Table 4). The other in the horizontal format was used to count an occurrence of each pattern for each student (see Table 5).



(a) Paloma Space Station (b) Alien Database

(c) Solar System Database (d) Other Tools

Fig. 1. Screenshots of *Alien Rescue* environment.

Table 1
Descriptions of in-game tools provided in *Alien Rescue*.

Tool categories	Tool	Tool functions
Tools sharing cognitive load	Alien database	Provides descriptions of six aliens' home planets and the characteristics of each species with 3D visuals.
	Solar system database	Provides (incomplete) information on our solar system that allows students to collect information such as species' habitat.
	Missions database	Provides information on past NASA missions, including detailed descriptions of probes used on these missions.
	Concepts database	Provides instructional modules on selected scientific concepts using interactive animations and simulations designed to facilitate conceptual understanding.
	Spectral database	Provides information to help students interpret spectra found in the Alien Database.
	Periodic table	Provides a periodic table of the elements.
Tools supporting cognitive process	Notebook	Allows students to take notes during problem-solving for collecting, summarizing, and integrating information.
Tools supporting otherwise out-of-reach activities	Probe design center	Provides an interactive tool for students to design probes that they will send to gather information about planets and moons in our solar system.
Tools supporting hypothesis testing	Mission control center	Allows students to review data from launched probes and to integrate information to test hypotheses.
	Message tool	Provides students with a way to submit their solution for each alien species. Students must also use the form to provide a rationale for their choice of alien habitat. Teachers can review and critique these solutions.

2.5. Data analysis

cSPADE algorithm (Zaki, 2000, 2001) in R package 'arulesSequences' was used to obtain frequent sequential patterns. The cSPADE algorithm mines constrained frequent sequences to discover sequences of items among objects in a given time period. One example used by Zaki was to discover the sequence patterns of website pages assessed by web users. A web user was considered as an object and a web page as an item. The algorithm uses a vertical id-list database as an input file where each transaction includes an object ID, event ID, item size and item(s). The sequential pattern mining algorithms have been developed in terms of efficiency and scalability; however, research contexts or domain knowledge are not often incorporated into the existing algorithms. To address these challenges, Zhou et al. (2010) suggested various ways of sequence modeling based on different research focuses: student-based sequence modeling, session-based sequence modeling, and object-based sequence modeling. This study aggregated students' navigation data by taking the student-based sequence modeling (see Table 6). Therefore, the identified frequent sequential patterns

Table 2
An example of navigation data.

Student ID	Tool	Action	Timestamp	Notes
5294	Probe design	Open	3/24/15 14:34	
5294	Probe design	Close	3/24/15 14:35	
5294	Probe design	Open	3/24/15 14:36	
5294	Probe design	Open probe	3/24/15 14:36	
5294	Probe design	Close	3/24/15 14:39	
5294	Alien database	Open	3/24/15 14:35	
5294	Alien database	Zoom in	3/24/15 14:35	
5294	Alien database	Zoom out	3/24/15 14:35	
5294	Alien database	Zoom in	3/24/15 14:35	
5294	Alien database	Zoom out	3/24/15 14:35	
5294	Alien database	Zoom in	3/24/15 14:35	
5294	Alien database	Zoom out	3/24/15 14:35	
5294	Alien database	Click	3/24/15 14:35	Species
5294	Alien database	Click	3/24/15 14:36	Our Solar System
5294	Alien database	Click	3/24/15 14:36	Species
5294	Alien database	Close	3/24/15 14:38	

students' navigation data each day to review all frequent patterns for each day and then to group the days into different stages as revealed by the data. Navigation data were created in cSPADE format and used to perform sequential pattern mining with the 0.5 minimum support of a sequence (denoted *min_sup*), indicating the results will only show the sequences that more than 50% of students used. We first reviewed a total number of transactions, a total number of students, and frequent elements across all sequential patterns each day. Since each tool has been categorized based on cognitive tool functions (see Table 1), we then analyzed the patterns based on how frequently the students used the four different cognitive tool categories subsequently or together each day.

To discover meaningful patterns across all stages, another sequential pattern mining analysis ($min\_sup > 0.5$) was conducted on the students' navigation data by each stage identified in the initial analysis. Pattern analysis for educational data requires the researchers to incorporate various kinds of user-specific constraints

Table 3
Examples of students' problem solutions.

Student ID	Alien name	Destination	Justification	Timestamp
5294	Sylcari	Europa	Europa Has the Water That Sylcari Needs to Survive. The Water Contains the Calcium that the Melk needs to grow. The Moon is Also a reasonable amount of Distance Away from the Sun So the melk can survive the Radiation.	3/27/15 20:32
5294	Jakala-Tay	Venus	Venus Has NO HYDROGEN, Has Sulfur, And Has Nitrogen	3/30/15 20:40

Table 4
An example of vertical format of navigation data.

Student ID	Tool
878768	Probe design
878768	Mission control
878768	Mission control
878768	Message
878768	Message
878768	Periodic table
878768	Message

Table 5
An example of horizontal format of navigation data.

Student ID	Tool 1	Tool 2	Tool 3	Tool 4	…
878768	Probe design	Mission control	Mission control	Message	…

Table 6
An example of an input file.

Student ID	Event ID	Item size	Tool name
862871	1	1	Alien database
862871	2	1	Probe design
862871	3	1	Notebook
862871	4	1	Alien database
862871	5	1	Solar database
862871	6	1	Solar database
862871	7	1	Spectra
862871	8	1	Periodic table
862871	9	1	Probe design
862871	10	1	Alien database
862871	11	1	Alien database
862871	12	1	Solar database

across a group of students can indicate frequent or common learning behaviors within this group.

The sequential pattern mining analysis was first performed on

such as a minimum/maximum length of a pattern, a minimum/maximum time difference between consecutive elements of a sequence, or certain sequences contained in a pattern or domain knowledge to a post hoc query language (Clark et al., 2012; Pei, Han, & Wang, 2007; Zhou et al., 2010). Using the literature as a guideline, we first specified several constraints for the cSPADE algorithm including 10 maximum number of elements of a sequence, 10 maximum number of items of an element of a sequence, and no maximum time difference between consecutive elements of a sequence. We did not specify a minimum number of elements since numerous patterns with a shorter length were expected within one stage. As observed in our previous studies (Liu, Kang, Lee, Winzeler, & Liu, 2015; Liu, Lee, Kang, & Liu, 2016), unlike other learning systems, students do not typically make a large number of "open" actions in this game context due to the limited amount of time per day (i.e., approximately thirty to forty minutes) spent in actually using the game. Other constraints were additionally applied to a post hoc query language to exclude non-meaningful patterns. Most of the super-patterns ($min\_sup > 0.5$) were excluded since the super-patterns can indicate the same or similar meaning with their sub-patterns within this game context. For example, a super-pattern, *Alien*→*Alien*→*Solar*, was combined with its sub-pattern, *Alien*→*Solar*, since both patterns can be interpreted as a learning behavior of matching planets information in Solar System Database with alien needs in Alien Database. Therefore, this constraint yielded only the sequences of length-2 as a frequent sequential pattern. Some patterns with the same items in a different sequential order were combined. For example, the *Alien*→*Solar* pattern was combined with the *Solar*→*Alien* pattern, since these two patterns do not differ from each other in terms of their cognitive functionality. In addition to the other constraints, we also applied the domain knowledge post hoc to identify significant patterns beyond all discovered patterns. In particular, the tool use patterns based on our previous studies of stimulated recall analysis and data visualization (Liu et al., 2009, 2015, 2016) were used to filter out irrelevant patterns. As observed in our previous studies, some patterns that are not meaningful are removed such as *Alien*→*Mission*, in which these two tools do not have any relation and can be used separately. By incorporating the various user-specific constraints, we developed a list of meaningful patterns across all stages.

To identify top frequent patterns in each stage, we counted this list of meaningful patterns using Python using the horizontal format with the sequence as shown in Table 5. We calculated the occurrences of each pattern by each student, and performed descriptive analyses on the occurrences of each pattern in each stage. Based on the measures of central tendency (e.g., median, mode, mean) and spread (e.g., quartiles, standard deviation) in each stage, the top 25% of patterns (i.e., 3rd quartile) were defined as frequent patterns, which included both sequential patterns and non-sequential patterns. The frequent patterns identified were then used in a multivariate analysis of variance (MANOVA) for group comparison of each stage. The students were separated into two groups based on their solution scores that represent the learning performance of students. As described previously, students were encouraged to submit multiple solutions for each alien species; therefore, they can get a full point (i.e., 1 point) for each alien with only one correct recommendation, and, as a result, more than 50% of the students got 6 points (i.e., a full score). To divide the students into the groups with an approximately equal sample size, high performance group ($n = 79$) included the students with a score of 6 and low performance group ($n = 76$) included ones with a score of 0–5. Since this study was conducted in a real classroom setting, not all students were able to submit at least one solution due to several possible reasons such as class absences or personal issues. For the group comparison, we removed this uncertainty by including only the student data which has logging information for the entire period of use as well as a solution score, which yielded a total number of 155 students. Five MANOVA tests were conducted separately, one for each stage, using the frequent patterns as dependent variables and the performance group as an independent variable. Multivariate F value (Wilk's λ) was used to determine the significant group differences in each stage. As for the significant stages ($p < 0.05$) discovered from the multivariate tests, a univariate test was conducted to evaluate the effect of group membership on each dependent variable ($\alpha = 0.0083$). Bonferroni correction (Bland & Altman, 1995) was used to control for the inflated family-wise Type I error rate when counteracting the problem of multiple comparisons (e.g., n hypotheses) at a statistical significance level of α/n (i.e., $0.05/6 = 0.0083$ in this study). Lastly, we examined student learning pathways for each performance group. As a result, one most frequent sequential pattern and one non-sequential pattern in each stage were selected as the frequent learning pathways in each stage for each group.

3. Results and discussion

3.1. What patterns emerge as students interact with various in-game tools?

The sequential pattern mining analysis (*min_sup* > 0.5) on the students' navigation data by each day revealed different problem-solving stages. During the first two days, the majority of the students accessed a variety of tools in different tool categories (see Table 1) such as Tool sharing cognitive load (e.g., Solar System Database) and then Tool supporting cognitive process (e.g., Notebook) or Tool sharing cognitive load (e.g., Alien Database) and then Tool supporting hypothesis Testing (e.g., Mission Control Center). Between Day 3 and Day 6, more than 50% of the students used the tools in the tool category, Tool sharing cognitive load. After that, during the 7th and 8th days, most of the students used Mission Control Center and Alien Database to compare the feedback in Mission Control Center with the aliens' needs and then started submitting their solutions via Message Tool. Between Day 9 and Day 11, more students submitted their solutions using Message Tool. Concurrently, they accessed not only Alien Database and Mission Control Center but also Solar Database. Lastly, the students focused more on using Mission Control Center and Message Tool during the last two days, rather than the tools under the Tools sharing cognitive load category. Based upon these emergent patterns, we identified five different stages: Stage 1 (Days 1–2), Stage 2 (Days 3–6), Stage 3 (Days 7–8), Stage 4 (Days 9–11), and Stage 5 (Days 12–13). The identified five stages indicated that certain tools were more dominantly used at certain problem-solving stages.

By examining the patterns that emerged from another sequential pattern mining analysis (*min_sup* > 0.5) on the students' navigation data by each stage, we identified a list of meaningful patterns across all stages. Table 7 provides the descriptions of each pattern. In general, two types of patterns were identified: (1) the patterns in a sequential order such as *MControl*→*Alien*, and (2) the patterns not in a sequential order such as *Alien*↔*Solar*.

We counted the occurrence of each pattern in each student's tool use sequence in each stage to generate final frequent patterns in each stage. As described above, the top 25% of patterns were considered as frequent patterns for each stage (see Table 8). During the first stage of the problem-solving process in *Alien Rescue*, the students used a variety of in-game tools. Interestingly, Notebook was a frequently used tool discovered only in the first stage, but not in other stages. Notebook is typically used to record important information about aliens' needs for easy access later. Classroom observations revealed that students often needed to complete paper worksheets provided by the teacher for grading purposes during the gameplay period (Liu, Wivagg, Geurtz, Lee, & Chang, 2012; Liu et al., 2015). Therefore, it is likely that in this study students first explored the functions of Notebook during the first stage and then recorded information on their worksheets during other stages of problem-solving and did not use Notebook after the first stage. Another unique pattern was *MControl*→*Alien*. This pattern indicates the majority of students used Alien Database after accessing Mission Control Center to compare results from a launched probe with alien needs. The pattern, *MControl*→*PDesign*, emerged as a frequent pattern in the first stage and then during the rest of stages except for the second stage. However, the students would not have any specific strategy to solve the problem during the first stage, in which they are expected to explore the environment by accessing a variety of tools (Liu & Bera, 2005; Liu et al., 2009). Therefore, *MControl*→*PDesign*, together with *MControl*→*Alien*, can be considered as the patterns for the purpose of exploration during the first stage.

The frequent patterns during the second stage, *Solar*→*Message* and *Alien*→*Message*, indicated that students started using Message Tool. Specifically, the students accessed Solar System Database or Alien Database to confirm if a planet met all of aliens' needs (Liu et al., 2015, 2016) and then wrote a relocation recommendation using Message Tool. Since there are a group of six alien species the students need to find a suitable home in our Solar System for, this pattern indicates that the students attempted to find a planet as the first alien's home during the second stage of problem-solving. The pattern, *MControl*→*Solar*, is another frequent pattern, which is consistent with our previous research that students reported revisiting often Solar System Database to look for other possible choices (Liu et al., 2009). This emerged pattern can indicate the students accessed Mission Control Center and then Solar System Database to compare results with information about planets and gather information about new planets because launched probes helped to eliminate previous planet choices.

During Stage 3, *MControl*→*PDesign*, was the most frequent

Table 7
An example of sequential pattern and non-sequential pattern.

Patterns		Description
Sequential patterns	*MControl → Alien*	Students open Mission Control Center and then Alien Database to compare results with alien needs.
	MControl → Solar	Students access Mission Control Center and then Solar System Database to compare results with information about planets and gather information about new planets because previous probes helped to eliminate previous planet choices.
	Alien → Notebook	Students open Alien Database and then the Notebook tool to record important information about alien's needs for easy access later.
	MControl → PDesign	Students open Mission Control Center to assess error messages and learn how to design appropriate probes, and then open Probe Design Center to remedy errors from previous probe and gather additional information about the planets that wasn't gathered with previous probes.
	MControl → Notebook	Students open Mission Control Center and then the Notebook tool to record newly gathered information from launched probes for easy access later.
	Solar → Message	Students open Solar System Database to double-check that planet met all of alien's needs and then write a relocation recommendation in the Message tool.
	Alien → Message	Students open Alien Database to double-check all of alien's needs and then write a relocation recommendation in the Message tool.
Non-sequential patterns	*Alien ↔ Periodic*	Students use both Alien Database and Periodic Table to gather specific information of chemical elements needed by aliens.
	Alien ↔ Solar	Students access both Alien Database and Solar System Database to get an overview of the problem and some general information during early stages. Students match planets with alien needs.
	PDesign ↔ Alien	Students open both Probe Design Center and Alien Database to look for specific things needed by aliens to design probes.
	PDesign ↔ Solar	Students use Probe Design Center and Solar System Database together to gather additional information about planets or look for what information is missing in the database and build probes based on the information.
	Notebook ↔ Solar	Students open both the Notebook tool and Solar System Database to record important information about planets for easy access later.
	Solar ↔ Periodic	Students use Solar System Database and Periodic Table together to look for additional concepts to better understand planets.
	Concepts ↔ Solar	Students access Concepts Database and Solar System Database together to look for additional concepts to better understand planets.

Note. Abbreviations were used to represent each tool as follows: Alien Database (Alien); Concepts Database (Concepts); Mission Control Center (MControl); Message Tool (Message); Probe Design Center (PDesign); Periodic Table (Periodic); Probe Launch Center (PLaunch); Solar System Database (Solar).

Table 8
Frequent patterns in each stage.

Stage	Top 25% frequent patterns	Number of students[a]	Mean (Standard deviation)[b]	Total occurrences
1	*MControl → Alien*	178	3.98 (*SD* = 3.36)	803
	MControl → PDesign	145	3.60 (*SD* = 4.16)	728
	Alien → Notebook	154	3.24 (*SD* = 3.55)	655
	PDesign ↔ Alien	169	3.98 (*SD* = 3.55)	803
	Alien ↔ Solar	190	3.57 (*SD* = 2.58)	721
	Notebook ↔ Solar	162	3.08 (*SD* = 3.55)	623
2	*Solar → Message*	152	2.72 (*SD* = 2.94)	550
	Alien → Message	151	2.58 (*SD* = 2.67)	521
	MControl → Solar	118	2.46 (*SD* = 3.16)	496
	Alien ↔ Solar	191	4.21 (*SD* = 2.90)	850
	PDesign ↔ Solar	139	2.81 (*SD* = 2.84)	567
	PDesign ↔ Alien	135	2.51 (*SD* = 2.78)	508
3	*MControl → PDesign*	132	2.45 (*SD* = 3.21)	487
	Alien → Message	144	2.15 (*SD* = 2.07)	427
	Solar → Message	131	2.06 (*SD* = 2.53)	409
	Alien ↔ Solar	161	2.47 (*SD* = 2.31)	492
	PDesign ↔ Alien	152	2.15 (*SD* = 1.88)	427
	PDesign ↔ Solar	143	2.04 (*SD* = 2.06)	406
4	*MControl → PDesign*	148	3.48 (*SD* = 3.95)	696
	Solar → Message	141	3.06 (*SD* = 3.72)	612
	MControl → Solar	145	2.97 (*SD* = 3.73)	593
	Alien ↔ Solar	173	3.70 (*SD* = 3.34)	740
	PDesign ↔ Solar	167	3.32 (*SD* = 3.21)	663
	PDesign ↔ Alien	167	3.21 (*SD* = 2.83)	641
5	*Solar → Message*	118	2.17 (*SD* = 2.92)	421
	MControl → PDesign	109	2.11 (*SD* = 3.07)	409
	Alien → Message	120	1.81 (*SD* = 2.43)	351
	Alien ↔ Solar	141	2.23 (*SD* = 2.56)	432
	PDesign ↔ Solar	121	1.76 (*SD* = 2.23)	341
	PDesign ↔ Alien	122	1.69 (*SD* = 2.01)	327

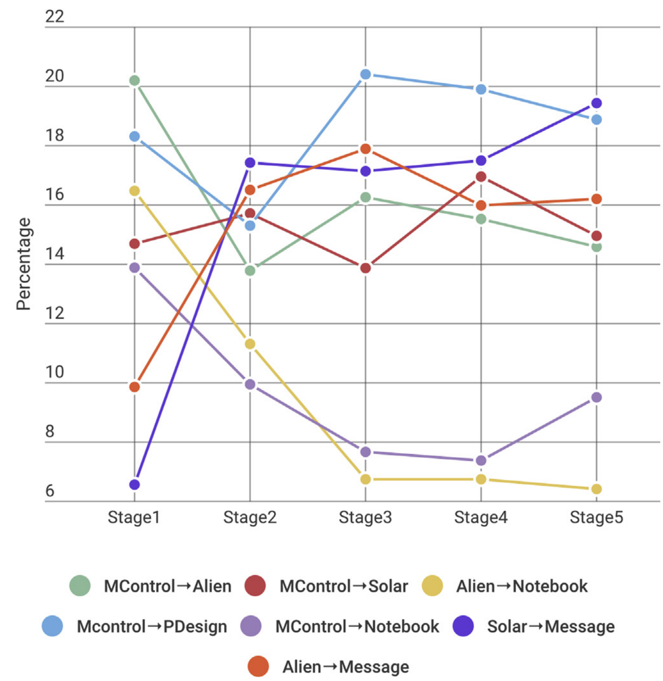
Note.
[a] Number of students who showed a pattern at least once in a stage.
[b] Mean = Occurrence/Total number of students.

pattern. It indicates students opened Mission Control Center to assess error messages and learn how to design appropriate probes, and then revisited Probe Design Center to remedy errors from the previously launched probes. The students repeatedly designed probes to gather additional information about the planets that was not gathered with previous probes for the purpose of finding a good home for all the six alien species (Liu & Bera, 2005; Liu et al., 2009). In addition, the students continued to ensure that a destination met all of aliens' needs in Alien and Solar System Databases and then wrote new relocation recommendation in Message Tool.

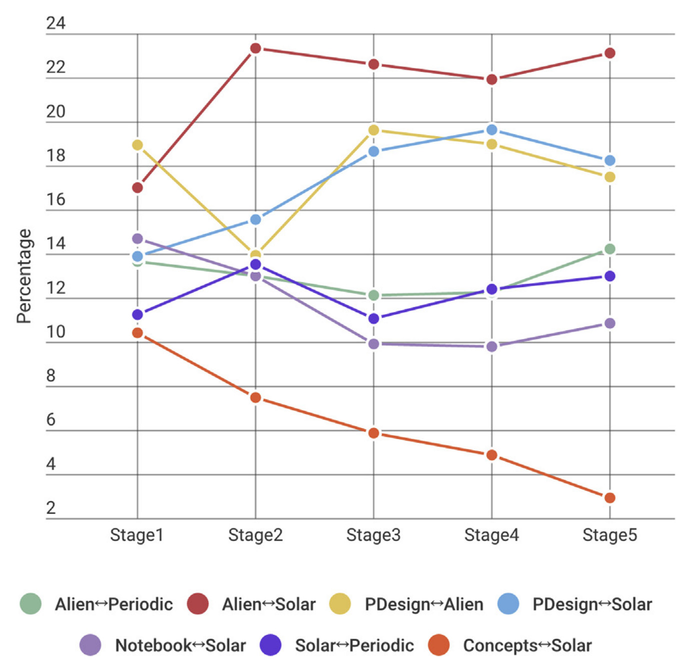
The frequent patterns in Stage 4 are similar with the ones in Stage 3; for example, *MControl*→*PDesign*, was the most frequent pattern for both stages. However, during Stage 4, more students showed this pattern at least once than the previous stage (n_{Stage3}_*MControl*→*PDesign* = 132, n_{Stage4}_*MControl*→*PDesign* = 148), and the students used these tools together approximately three times on average (Mean$_{\text{Stage3}}$_*MControl*→*PDesign* = 2.45, Mean$_{\text{Stage4}}$_*MControl*→*PDesign* = 3.48). Another frequent pattern, *MControl*→*Solar*, indicates that more students viewed the data gathered from the launched probes in Mission Control Center. As discussed above, this pattern indicates more likely that the students received error messages in Mission Control Center and needed to interpret the results by investigating why their probe failed. To examine the results, the students revisited Solar System Database and considered other probe design options such as probe types, power sources, or instruments, or other destination options as suitable homes for the alien species. Compared to Stage 2, the increasing use of the *MControl*→*Solar* pattern (n_{Stage2}_*MControl*→*Solar* = 118, n_{Stage4}_ *MControl*→*Solar* = 145) suggests that more students learned these tools were critical to gather additional information about the planets that was not gathered with previous probes or find new homes that might be a good match with alien needs, when previous planet choice was eliminated based on the probe results. In addition, the *Solar*→*Message* pattern indicates that more students proceeded toward the evaluating process by ensuring the planet they selected truly met all of the aliens' needs.

During the last stage, the frequent patterns, *Solar*→*Message* and *Alien*→*Message*, showed the students returned to Solar System Database or Alien Database to double-check if the planet met all of aliens' needs. There is a decrease in the number of these patterns toward the final stage. *MControl*→*PDesign* is another pattern that showed a decreasing tendency. For example, only 60% of the students (n_{Stage5}_*Solar*→*Message* = 118) showed the pattern, *Solar*→*Message*, which suggests that the other 40% of the students might already complete their mission by this time; therefore, not all students needed to gather additional information by designing a new probe or submit a solution. In support of our previous research (Liu & Bera, 2005; Liu et al., 2009), the emerged frequent patterns over different stages of problem-solving highlighted the concurrent and repeated use of a set of tools while the students were engaged in integrating and evaluating information.

We further examined the tool use trend over the five stages. Fig. 2 showed the occurrences of major discovered patterns (i.e., sequential patterns and non-sequential patterns) over the five stages. The first stage of problem-solving can be considered as the exploring stage since the occurrences of most of the patterns increased in value at a greater rate from Stage 1 to Stage 2; however, the changes over the rest of the stages were more stable. Such tendency thus suggests the students' uses of the in-game tools were more strategic from the second stage on, as shown in previous studies (Liu & Bera, 2005; Liu et al., 2009). The student behaviors of recording the information of alien needs and results from probes (i.e., *Alien*→*Notebook*, *MControl*→*Notebook*) were mostly not found since the third stage. Aside from the in-game activities, the teachers in this study provided several worksheets for students to record what they found from the tools such as the alien needs or planet information to support research process (Liu et al., 2012, 2015). This could explain the decreasing tendency of recording behaviors. The students' use of Mission Control Center and then Probe Design Center (*MControl*→*PDesign*) peaked on Stage 3 and was relatively stable during the rest of the stages. In addition, the occurrences of the behavior pattern of Alien Database and Solar System Database (*Alien*↔*Solar*) showed the similar tendency, which increased from



(a) Occurrences of sequential patterns



(b) Occurrences of non-sequential patterns

Fig. 2. Sequential and non-sequential pattern trends over five stages. (a) Occurrences of sequential patterns. (b) Occurrences of non-sequential patterns.

Stage 1 to Stage 2 and remained fairly static at approximately 23%. Similarly, the occurrences of two non-sequential behavior patterns—Probe Design Center with Alien Database (*PDesign*↔*Alien*) and Probe Design Center with Solar System Database (*PDesign*↔*Solar*)—increased over five stages, which indicate the students repeatedly designed probes by comparing the information provided in the two databases, suggesting the students' continuous inquiry process over time. All in all, during the early stages, the students tended to conduct research by finding out the information needed to further determine a suitable home for one alien species, formulate and test hypotheses by interacting with Probe Design Center, interpret returned data in Mission Control Center, and then generate a solution using Message Tool. Learning occurs as students engage with the process of solving the complex problem in the game (Liu et al., 2015, 2016); therefore, once the students moved through the entire problem-solving process for the first alien, they were more strategic in use of the same sets of tools to solve the problem over the rest of stages.

Previous research revealed the problem-solving process used in *Alien Rescue* can be grouped into different stages. Liu and Bera (2005) investigated the use of in-game tools across five contextual problem-solving stages (i.e. initial exploring, background research, hypothesis generation, hypothesis testing, and solution generation) through cluster analysis. A follow-up study by Liu et al. (2009) proposed the four conceptual problem-solving stages: (a) understanding the problem, (b) identifying, gathering, and organizing information, (c) integrating information, and (d) evaluating the process and outcome. The results indicated that students were strategic in their tool usage throughout all stages of the gameplay experience. For example, during the early stages, students used the tools sharing cognitive process and tools sharing cognitive load more than tools supporting otherwise-out-of-reach activities and hypothesis testing, and that the latter tools were used more in the later stages. The findings of this present study support the students' strategic tool use over different stages, indicating that the students were engaged in the process of scientific inquiry by exploring the various in-game tools, discovering the capability of each tool, and developing their own strategies of the effective tool use such as when and how different tools can be used together to move through the process of problem-solving. However, in contrast to the previous studies, the emerged patterns and pattern trends as revealed in this study (see Table 8 and Fig. 2) indicated that the students were likely to explore the game environment during the first stage and then, from the second stage, begin to go through the entire problem-solving process including background research, hypothesis generation, hypothesis testing, and solution generation. Since students were encouraged to submit multiple solutions for each alien species, they tended to generate a solution for the first alien species early in the problem-solving process. Although *Alien Rescue* aims to teach sixth-grade space science in about fifteen 50-min class sessions, teachers can adjust the sessions depending on their needs and classroom situations. Regardless of days or stages, students can access any tools on any day depending on their learning strategies. While the existing research on problem-solving processes used in *Alien Rescue* was based on five contextual or four conceptual stages in which different classroom situations were not considered, the data-driven results from this present study identified five stages of problem-solving process of *Alien Rescue* based upon the sequential tool usage patterns.

3.2. Sequential patterns of learning performance groups

In order to find a right solution for each alien, students are expected to use in-game tools repeatedly. An occurrence of each tool use can be varied in students with different strategies or learning performances. Therefore, we further examined sequential patterns of different learning performance groups. The students were classified into high ($n = 79$) and low ($n = 76$) performing groups based on their solution scores. A one-way MANOVA test was performed to determine if there were any mean differences in the occurrences of frequent patterns between two groups in each stage. Among all five stages, Stages 2, 3, and 5 showed the significant results (see Table 9). Therefore, the results indicated that the performance group membership did have the significant effect on the occurrences of different frequent patterns in these stages. A set of univariate tests was conducted for each of these three stages. The *Solar→Message* pattern was the only pattern found significant over these three stages. Specifically, during Stage 2, there was a significant effect on the occurrences of *Solar→Message* pattern between two groups [F (1, 153) = 7.297, p = 0.008]; in Stage 3, [F (1, 153) = 7.993, p = 0.005]; in Stage 5, [F (1, 153) = 10.173, p = 0.002].

Table 9
Multivariate tests results of five stages.

Stage	Effect Value (Wilk's Lambda)	F	Hypothesis df	Error df	p
1	0.938	1.623	6	148	0.145
2	0.917	2.236*	6	148	0.043
3	0.916	2.255*	6	148	0.041
4	0.925	2.001	6	148	0.069
5	0.881	3.333*	6	148	0.004

Note. *$p < 0.05$.

To better understand learning behavior patterns by a different performing group, we developed learning pathway diagrams as shown in Figs. 3 and 4. We first determined the most frequent pattern of each performing group in each stage by considering total occurrences, average occurrence, and standard deviation of each pattern in each stage. Then, each performing group's learning pathway diagram was developed based on the most frequent patterns. In particular, the game environment has a two-layer interface: the first layer consisting of Alien Database, Probe Design Center, Mission Control Center, and Communication Center (i.e., Message Tool) and the second layer consisting of Solar System Database, Missions Database, Concepts Database, Spectral Database, Periodic Table, and Notebook. Students can overlay each tool in the second layer with any tool in the first layer. The tools in the first layer are signified with a square and the tools in the second layer are signified with octagon (see Figs. 3 and 4). In addition, any sequential behavior patterns are signified with an arrow pointing to its direction, and any non-sequential behavior patterns are signified with a dotted line. It is worth noting that the students in the high performing group showed obviously the same pattern (i.e., *Solar→Message*) since the second stage; that is, the high performing students frequently accessed Solar System Database to double-check if a planet met all of alien's needs before writing a relocation recommendation in Message tool. The design of *Alien Rescue* intentionally allows multiple possible answers and multiple placements (i.e., suitable homes in our Solar System) for each alien. The teachers thus encouraged the students who already finished one placement for each alien to submit additional placements. Additionally, they completed exploring the game environment and testing hypotheses mostly during the first stage (i.e., *MControl→Alien*; *Alien↔Solar*). This finding indicated these high performing students were more likely to finish their research phase earlier than the other group.

Conversely, the low performing students showed more a variety of tool use patterns over the five stages (see Fig. 3 (b)). Fig. 4 provides the learning pathways of the low performing students for each stage. Noticeably, the low performing students tended to access more often Probe Design Center over the entire period, but less often Solar System Database than the other group did. In particular, they tended to access both Probe Design Center and Mission Control Center repeatedly over the entire period rather than during the stages when the use of these tools are more pertinent according to the problem-solving stages the students were at. This is consistent with our previous research (Kang, Liu, & Liu, 2017; Liu et al., 2015, 2016) that noted that students with lower performance scores seemed to use the most fun tools of all in-game tools such as Probe Design and Mission Control Centers, which allow students to design a probe as a scientist and therefore preserves the

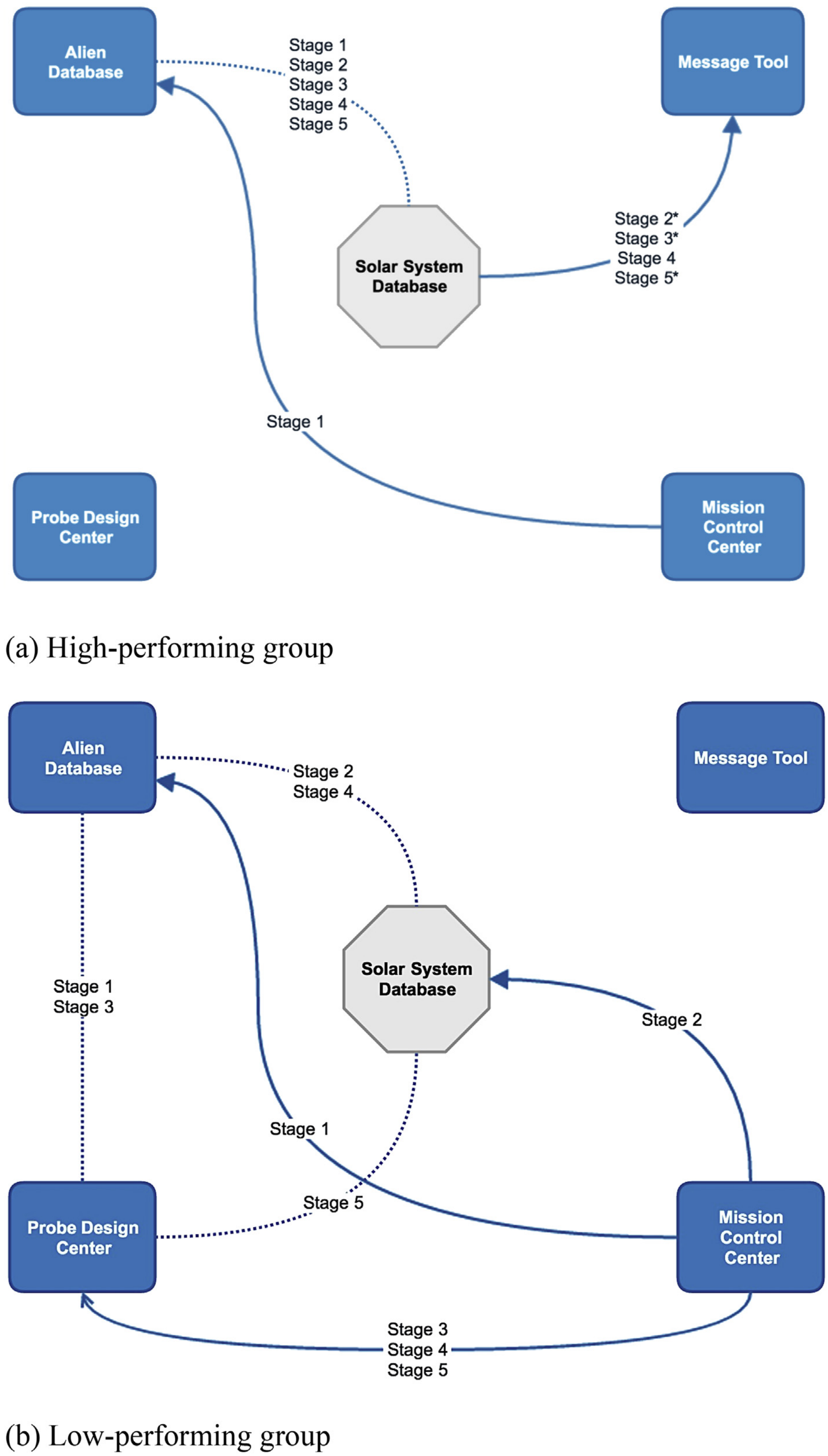


Fig. 3. Learning path diagram of performance groups. (* indicates a significant pattern identified from MANOVA analyses). (a) High-performing group. (b) Low-performing group.

authenticity of learning experience.

Students are often challenged to gather information embedded in various in-game tools and integrate the information in the process of solving this complex problem for each alien. In order to complete these tasks, strategic use of these tools is central. This study confirmed that problem-solving strategies were differently used between low and high performing students within this environment. Literature has indicated expertise as a potential

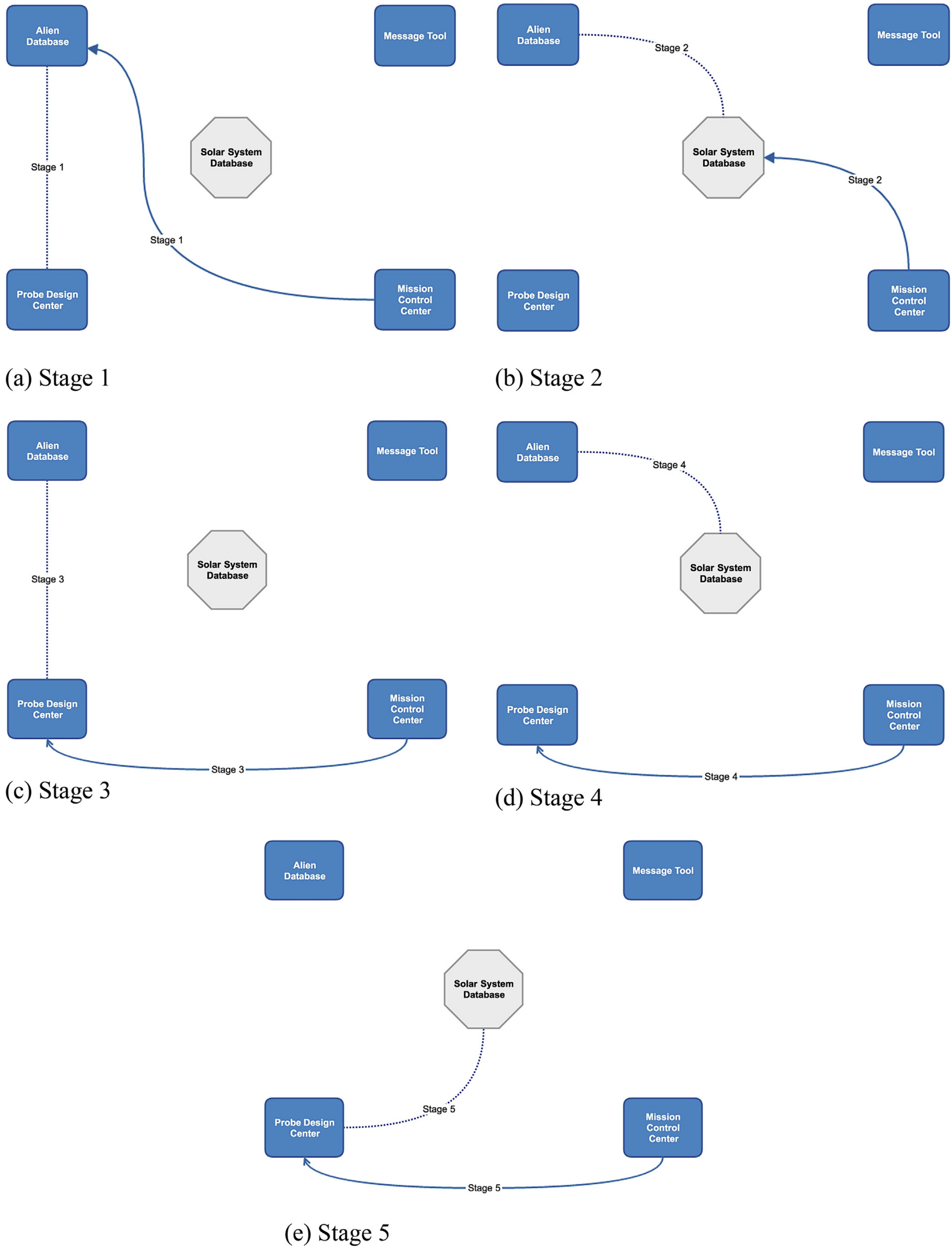


Fig. 4. Learning path diagram of low-performing group over the five stages.

influence on the process of problem-solving (Jonassen, 2000; van Merriënboer, 2013). Rule application and competency are a measurable change found in learners' action sequences during the problem-solving process (Dreyfus, 2004). For instance, novices first tend to follow rules without thinking carefully; eventually, they learn how to apply rules correctly over time as well as attain more competencies. In this present study, the findings indicate the low performing students spent longer time or struggled to find out new information that is not provided in other tools. This can also explain their needs of redesigning appropriate probes over time to gather additional information about a planet that was not gathered with previous probes. Experts show a working forward strategy by proceeding toward sub-goals, in which they constantly apply the information they gathered to attain each sub-goal; in contrast, novices show a working backward strategy by first setting a goal of the problem and then proceeding backward an initial state (Chi et al., 1981). The repeated use of the *Solar→Message* pattern by the students with higher performance suggest that they tended to work forward toward each sub-goal, which is to find out suitable homes for each alien in this game context. During the initial stage, they may have figured out Solar System Database as a critical tool to solve the problem, and used this tool more strategically over the rest of stages.

4. Conclusion

This study built upon our previous research examining students' tool use patterns including what tools students used over problem-solving processes and why they used these tools. The findings of this study confirmed the results from the previous research (using *ex situ* data such as interviews) and provided an analytical approach to understand students' sequential behavior patterns using *in situ* gameplay data. Prior research has identified students' learning patterns in the game environment over different problem-solving stages using general game metrics such as frequency or duration of each tool use (e.g., Liu et al., 2009, 2015, 2016). In this present study, we performed sequential pattern mining to analyze what tools students frequently used in a sequence to solve the problem. Using sequential pattern mining allows us to identify different sets of days as separate problem-solving stages, and discover frequent patterns within each stage—identified in the initial pattern mining analysis. That is, different stages are identified empirically based upon the data. In addition, separate sequential pattern mining was conducted, because one challenge is that sequential pattern mining cannot provide when sequences of events actually occur (Clark et al., 2012). If we perform one sequential pattern mining using the entire gameplay data, the patterns would not be able to discover when or why the students actually access these tools in such sequences.

Zhou et al. (2010) suggested that research contexts or domain knowledge should be incorporated into the existing sequential pattern mining algorithms. Therefore, this study considered several constraints such as super-pattern constraint (i.e., only sub-pattern), sequence modeling constraint (i.e., student-based sequence modeling), domain knowledge constraint to exclude non-meaningful patterns in this specific game context. The frequent sequential and non-sequential patterns identified in each stage indicate more in-depth tool usage patterns over the problem-solving process as follows: (1) During Stage 1, students explore the environment by accessing various tools; (2) then, students mainly conduct research by seeking for the information needed to determine a suitable habitat for each alien and also begin to submit a relocation recommendation for the first alien during Stage 2; (3) after that, during Stage 3, students assess additional information to test their hypotheses by interacting with Probe Design Center and interpret returned data in Mission Control Center and with Alien Database to match aliens' needs; (4) during Stage 4, the students continue to formulate and test hypotheses for the rest of aliens and return to Solar System Database to find new planets that might be a good match; and (5) lastly, during Stage 5, they double-check all the information to finalize a solution for the rest of aliens. These in-depth pattern analyses indicate students' engagement in the process of scientific inquiry using various in-game tools embedded in SG.

Procedure knowledge in addition to domain knowledge is another key component to successful problem-solving (Chi et al., 1981; Gick, 1986). Research on problem-solving shows that learning to solve scientific problems involves a conceptual change only achieved when students possess both conceptual and procedural knowledge—central components of twenty-first century skills (Clarke-Midura, Dede, & Norton, 2011; National Research Council, 1996; Quellmalz, Timms, & Schneider, 2009). Understanding students' behavior patterns within SG will facilitate students with different levels of performance to acquire procedural knowledge (Hou, 2015; Loh, 2012). This study investigated the students' problem-solving strategies by examining the frequent sequential patterns between low-and high-performing students. The findings confirmed the low-performing students were challenged to find out information embedded in different in-game tools and integrate the information in the process of solving this complex problem (Kang et al., 2017; Liu et al., 2009, 2015, 2016). In addition, the high-performing students showed more strategic tool use patterns; that is, they tended to work toward several sub-goals of determining suitable homes for each alien (Chi et al., 1981; Dreyfus, 2004). The emergence of serious games analytics enables researchers to trace students' sequences of actions during the problem-solving process within the SG environment as evidence of their learning performance (Loh & Sheng, 2014; Schmidt & Lee, 2011). Such tracing results can promote diverse problem-solving strategies and identify challenges students with different expertise may face.

In this study, we first conducted data mining technique of sequential pattern mining to discover students' learning patterns through gameplay data. Second, we combined sequential pattern mining and multivariate analysis of variance (MANOVA) to analyze frequent patterns based on different performance groups and different stages. In addition, the results of frequent patterns are visualized as learning pathways of low- and high-performing groups. Such an integrated method will not only provide in-depth learning pathways of student performance, but also promote the understanding of problem-solving strategies of students with different learning characteristics in SG context.

5. Limitations and future directions

This study is limited in that using only *in situ* data cannot provide the context of the gameplay such as why a learner is performing a certain action or if a learner is having fun or not (Wallner & Kriglstein, 2013). Due to the diverse issues in real classroom situations such as student absence, there are a few factors this study did not take into consideration: (1) a concurrent tool usage which indicates more than one tools accessed together during the same time period and (2) time difference between consecutive elements of a sequence which may indicate students open the tools shown in a sequence consecutively in different days within a stage. Given the challenge of sequential pattern mining such as inability of analyzing timing of events (Clark et al., 2012), we hope in the future such concurrent pattern analysis will reveal an in-depth look of whether the patterns are relevant (e.g., students' latent strategies of problem-solving) or the result of unskilled mouse control.

The understanding of what tools students most likely use in a sequence to solve the problem can provide insights of designing effective learning environment by eliminating undesired clicks or actions. For example, the pattern, *PDesign↔Alien*, indicates that students often accessed Alien Database together with Probe Design Center. Since these tools are in different layers—that is, two tools cannot overlay, the frequent use of this set of tools might cost unnecessary time. With the findings from this study, we hope to improve the game environment by eliminating undesired outcomes such as inappropriate tool use.

One challenge of open-ended serious games is to identify students' learning progression, in which they can take diverse paths to solve a problem (Squire, 2008). Our findings suggest that pattern analysis can provide an opportunity of tracking in-depth learning process in the context of SG, and diverse patterns can be used as an indicator of student performance. We are in the process of developing predictive models with sequential patterns as predictors of student achievement or failure, which can be applied at a specific context of game learning environment. In addition, we are currently developing a teacher's dashboard which presents just-in-time gameplay data to allow for teachers' timely pedagogical interventions aiming to monitor and facilitate students' learning process. The findings of the productive tool use shown by high-performing students can guide low-performing students to higher performance throughout their problem-solving process. For example, if a student has not accessed certain tools at a certain time, a teacher can intervene in the student's tool use relevant to the problem-solving stage. Future development of teachers' dashboard can be also customizable to cater to different instructions such as individual or group work. For instance, in the case where a group work is preferable, the teacher's dashboard can present the similarity or dissimilarity of sequential patterns between students in a group to facilitate their learning progression through collaboration.

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