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Uncovering students' problem-solving processes in game-based learning environments

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A B S T R A C T

As one of the most desired skills for contemporary education and career, problem-solving is fundamental and critical in game-based learning research. However, students' implicit and self-controlled learning processes in games make it difficult to understand their problem-solving behaviors. Observational and qualitative methods, such as interviews and exams, fail to capture students' in-process difficulties. By integrating data mining techniques, this study explored students' problem-solving processes in a puzzle-based game. First, we applied the Continuous Hidden Markov Model to identify students' problem-solving phases and the transition probabilities between these phases. Second, we employed sequence mining techniques to investigate problem-solving patterns and strategies facilitating students' problem-solving processes. The results suggested that most students were stuck in certain phases, with only a few able to transfer to systematic phases by applying efficient strategies. At the beginning of the puzzle, the most popular strategy was testing one dimension of the solution at each attempt. In contrast, the other two strategies (remove or add untested dimensions one by one) played pivotal roles in promoting transitions to higher problem-solving phases. The findings of this study shed light on when, how, and why students advanced their effective problem-solving processes. Using the Continuous Hidden Markov Model and sequence mining techniques, we provide considerable promise for uncovering students' problem-solving processes, which helps trigger future scaffolds and interventions to support students' personalized learning in game-based learning environments.

1. Introduction

Problem-solving is defined as a cognitive process of analysis and transformation guided by a particular goal when the solution is not obvious to problem solvers (Lovett, 2002; Mayer & Wittrock, 2006; Wang & Chiew, 2010). Problem-solving skills are the essential competencies that students must possess in the twenty-first century (Khoiriyah & Husamah, 2018). Students are no longer rewarded merely for what they know, but also for what they can do with what they know. Problem-solving is at the heart of this, the capacity of mobilizing ingenuity and creativity to solve complex problems with learned knowledge (Csapó & Funke, 2017).

With attractive storylines and appealing tasks, game-based learning environments have been widely shown to improve students' engagement and perceived achievement (Plass, Homer, & Kinzer, 2015). In games, the content is typically designed with problem-solving tasks and challenges. Students need to bring out the implicit knowledge embedded in problems to construct more general and applicable knowledge structures (ter Vrugte & de Jong, 2017). Recently, about 1.5 billion students have been compelled to

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learn from home because of the COVID-19 pandemic (Hill, 2020). Owe to the availability and potential in enhancing students' problem-solving practices, learning games have been gaining increasing attention as an efficient context that enables diverse students to engage in complex skill acquisition during the hardest time (Wati & Yuniawatika, 2020).

Problem-solving processes in learning games can be seen as a set of inner-associated phases, wherein students employ different strategies to solve the problems (Price, Kim, Burkholder, Fritz, & Wieman, 2021; Rowe et al., 2021). A general problem-solving process may begin with a number of trials and plans, then recognize and understand the underlying rules of games, then design and implement appropriate solutions, and finally evaluate and generalize these solutions (Wang & Chiew, 2010; Wiltshire, Butner, & Fiore, 2018). Different games may involve different problem-solving processes. For example, a prior study (Sawyer, Rowe, Azevedo, & Lester, 2018) found three problem-solving phases when students engaged in a narrative-centered game (Rowe et al., 2009): tutorial, information gathering, and diagnosis. These problem-solving phases did not occur in isolation; rather, students utilized strategies (e.g., seeking help, negotiating with peers, and searching on the website) to move into higher phases in a given task (Intaros, Inprasitha, & Srisawadi, 2014; Kotovsky & Fallside, 2013).

Uncovering students' problem-solving processes is essential because problem-solving phases and strategies reflect students' knowledge mastery and skill acquisition in learning games (Yavuz, Yasemin, & Arslan, 2017). On the one hand, it helps instructors assess students' knowledge acquisition and provide appropriate scaffolds timely. On the other hand, if students are able to get out of the stuck moments and transfer to higher phases, educators can determine the most practical strategies for promoting these transitions. In games, implicit knowledge is settled in complex scenarios wherein students build their intelligence and competencies stealthily (Rowe et al., 2021). It is difficult to uncover students' problem-solving processes since they are considered "hidden". Current assessments such as exams and self-reported surveys do not measure students' real-time learning processes, and would be extremely time-consuming at scale (Rowe, Asbell-Clarke, Cunningham, & Gasca, 2017; Tissenbaum, 2020). Since game-based learning can generate meaningful gameplay log data, it provides rich evidence of students' problem-solving processes (Ke, Xie, & Xie, 2016; Rowe et al., 2021). For example, a variant of clustering analysis (Kang, An, Yan, & Liu, 2019) was conducted to investigate students' daily gameplay actions and examine the processes of collaborative problem-solving. Cui, Chu, and Chen (2019) modeled students' gameplay data by Bayesian networks to track their problem-solving performance. Based on prior studies, leveraging techniques such as machine learning and data mining on gameplay data can efficiently enable automatic recognition and fine-grained understanding of students' problem-solving behaviors (Asbell-Clarke, Rowe, Almeda, Edwards, Bardar, Gasca et al., 2021).

Due to students' problem-solving phases are not observable, employing a direct representation of these latent phases with probabilistic automation shows promise for interpreting students' problem-solving processes. Hidden Markov Model (HMM) (Rabiner & Juang, 1986) is a data mining approach that provides great affordance for analyzing students' problem-solving processes as phases-based models (Rabiner, 1989). HMM can be learned from students' observed gameplay sequences to describe a series of probabilistic phases involving many activities that evolved in a certain task. However, the observation distribution in a standard HMM is single-dimensional and discrete (Chen, Wilcox, & Bloomberg, 1995). It is insufficient for numerous multidimensional meaningful information generated from students' complex learning interactions. In learning games, each gameplay action may include many features to define the specific tasks and students' behaviors. The Continuous Hidden Markov Model (CHMM) (Rabiner, Juang, Levinson, & Sondhi, 1985) modeled by Gaussian models allows the observations to be multidimensional and continuous. In this study, since the specific puzzle-based game includes hundreds of attributes to describe students' gameplay actions, we apply CHMM to model students' problem-solving processes to efficiently cope with their multidimensional learning interactions.

At the same time, CHMM overlooks many common activities and specific variations in students' sequential behaviors. Sequential analysis (e.g., sequential pattern mining) (Mooney & Roddick, 2013) is a supplemental technique that provides a fine-grained analysis of what strategies students used and how they applied these strategies in different problem-solving phases. By exploring the frequent patterns in students' learning interactions, we can examine effective strategies (i.e., patterns) for facilitating organized problem-solving processes. For example, a previous study (Clark, Martinez-Garza, Biswas, Luecht, & Sengupta, 2012) showed that guessing a solution was found at the beginning of students' problem-solving processes, while deriving a solution step by step was manifest at the mature phases. Combining CHMM and sequence mining techniques can reveal elaborate problem-solving trajectories and highlight informative transitions in learning games, which helps trigger efficient scaffolds for students' personalized problem-solving practices.

In response, this study proposes an integrated data mining method to uncover students' problem-solving processes. Specifically, we analyze the gameplay log data of 30 students who played with a specific puzzle called ***Pizza Pass***, from a game-based learning environment—***Zoombinis***. First, we use CHMM to identify students' problem-solving phases and estimate the transition probabilities between these phases (i.e., from **Trial and Error** to **Systematic Testing**). Next, we explore students' problem-solving strategies in different phases by employing a novel combination of sequence mining techniques. The contributions of this work are threefold: (1) presenting how to analyze gameplay actions with multidimensional features by integrating CHMM and sequence mining; (2) depicting students' problem-solving processes and revealing the strategies that facilitate effective transitions and systematic problem-solving; (3) locating "stuck" moments that require external interventions to support students' personalized learning in games. The following research questions guided this study:

- How to apply data mining techniques to uncover students' problem-solving processes in ***Zoombinis***?
- How do students advance their problem-solving processes in ***Zoombinis***?

2. Theoretical foundations & related work

2.1. Problem-solving processes in game-based learning environments

Problem-solving process is commonly characterized as a cognitive activity that reveals conscious exploration and integration of information gained (Frensch & Funke, 1995). Theoretical foundations of problem-solving vary depending on the types of problems (Jonassen, 1997). For example, well-structured problems are constructed on information-processing theory (Simon, 1978), while ill-structured problems share assumptions with constructivism and situated cognition (Jonassen, 2000). To date, most of the developed conceptual frameworks of problem-solving focus on mathematics and science education. For instance, Singer and Voica (2013) proposed a framework in math education that included four phases: decoding, representing, processing, and implementing. Due to the complexity and diversity, problems in different games may have different structures and involve various knowledge, which can influence students' problem-solving processes (Dörner & Funke, 2017). Currently, there is no consensus on the descriptions and definitions of problem-solving processes in games. For example, building on the flow theory (Csikszentmihalyi, Abuhamdeh, & Nakamura, 2014), a study (Thompson et al., 2021) developed a problem-solving framework that included four phases in an immersive cross-platform game: orientation, representation, planning, and selection. Liu, Zhi, Hicks, and Barnes (2017) introduced a five-phase framework in a programming game: identification, representation, selection, implementation, and evaluation.

To conceptualize problem-solving frameworks in games, examining the learning attributes of games is crucial. Garris, Ahlers, and Driskell (2002) introduced a practical game-based learning framework. This framework suggests that students' motivation and learning processes are reflected in recognizing the underlying rules of problems, which requires a variety of strategic knowledge and problem-solving skills in learning games. Using constructivism as the theoretical underpinning, Pellas and Vosinakis (2017) further extended this framework which included three phases to understand students' problem-solving behaviors in simulation games. Even though problem-solving processes might vary based on different learning games (Shute, Wang, Greiff, Zhao, & Moore, 2016), we can generally summarize the features of problem-solving processes in games. Problem-solving in game-based learning environments can be defined as a process that requires students to repeatedly understand and apply available knowledge or strategies to approach the solutions. Specifically, students need to decompose the problem, understand the implicit knowledge, recognize gameplay patterns, employ some strategies to design solutions, and finally implement the solutions with critical evaluation. These phases may be described differently in particular games, but they all assume that the efficient problem-solving process in learning games begins with lower phases and eventually progresses to higher ones.

Zoombinis is a puzzle-based game in which students are required to involve in ill-structured problems to construct mathematics concepts and mobilize cognitive and behavioral skills (Eseryel, Law, Ifenthaler, Ge, & Miller, 2014; Plass et al., 2015; Spires, Rowe, Mott, & Lester, 2011). Previous study (Rowe et al., 2021) has established a problem-solving framework with six phases in this specific game. Students' problem-solving processes in ***Zoombinis*** are highly iterative among these phases as new problems and contexts are encountered. In this study, we particularly focus on four of them wherein students might engage in stuck loops or challenging transitions:

- **Trial and Error**: There is no evidence of ordered or planned behaviors shown in students' gameplay. Actions are independent of the previous one and not testing any hypotheses.
- **Systematic Testing**: Evidence shows that students are trying to reveal the underlying rules with ordered and planned gameplay behaviors. Actions are dependent on the previous one.
- **Implement Solution**: Completing a pattern of solutions with one or whole dimensions of the rules solved.
- **Generalize Solution**: Evidence shows that a sequence of strategic actions is repeated across multiple attempts to solve one or more puzzles.

Trials allow students to familiarize themselves with games, which is the premise of recognizing problems and designing strategic solutions. Systematic analysis indicates that students develop efficient strategies and systematically test at least one dimension of the given problem. If students implement their answers correctly, they can work on multiple threads and finally generalize their solutions to future puzzles.

Viewing problem-solving as an amalgamation of a number of phases, students can transfer to higher phases with efficient strategies. Even though these strategies may not guarantee solutions, they are considered as imperative guidance in students' problem-solving processes (Gick, 1986). In other words, applying strategies is essential whenever students attempt to further their problem-solving practices (Gick, 1986; Tuma & Reif, 1980). Research on ***Zoombinis*** has already manually identified some strategies. For example, Rowe et al. (2017) found that testing one dimension of a certain problem was pragmatic when students transferred from random trials to systematic problem-solving. However, manually labeling students' problem-solving strategies would be extremely time-consuming, particularly when the participants are in large numbers. Integrating data mining techniques can automatically and dexterously uncover profitable strategies that students use to get out of their stuck persistence.

2.2. Methods of uncovering problem-solving processes in game-based learning environments

Understanding students' problem-solving in game-based learning is much more difficult than in traditional learning contexts. The characteristics of game-based learning permit students to develop complicated and dynamic learning trajectories (Al-Azawi, Al-Faliti, & Al-Blushi, 2016; Ifenthaler, Eseryel, & Ge, 2012) and solve problems through various paths. Exams or surveys fail to track in-process difficulties or knowledge changes in students' learning processes (Hacke, 2019; Gök & Sỳlay, 2010). Analyzing students' gameplay videos or their think-aloud data is widely used in case studies, but it would be cumbersome in games which involve multidimensional learning interactions (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, Feltovich, & Glaser, 1981; Montague & Applegate, 1993; Nakhleh, 1993). In the case of data mining approaches have been booming in educational research in recent years, many empirical studies focus on exploring students' problem-solving processes with these methods (Angeli & Valanides, 2013; Fern, Komireddy, Grigoreanu, & Burnett, 2010; Vendlinksi & Stevens, 2002). Data mining approaches make it possible to analyze students' extensive learning actions in real-time and automatically, especially at scale (Nájera & de la Calleja Mora, 2017). In games, students' gameplay actions are operationalized as time spent on problems (Emerson, Cloude, Azevedo, & Lester, 2020). With multiple features, gameplay log data records extensive details of students' learning processes, making it more predictive and informative for problem-solving assessment.

For example, Kang et al. (2019) divided students into three clusters based on the similarity coefficient of their problem-solving sequences. The authors summarized each cluster's characteristics, which can be used to design positive interventions in the future. Another study (Wen et al., 2018) modeled students' problem-solving processes in a simulation game through supervised and unsupervised Lag Sequential Analysis (LSA). Specifically, the supervised LSA addressed the differences between students' groups regarding their problem-solving behaviors, while the unsupervised LSA identified hidden stages of students' problem-solving. Besides, Liu et al. (2017) examined students' problem-solving styles and strategies by clustering their debugging gameplay actions. Bauer and Flatten (2017) found some key patterns and explained how these patterns distinguished experts in a scientific-discovery game by devising an iterative visualization-based method. However, most of current studies pay attention to developing and improving algorithms, while the educational findings are brushed aside. This study demonstrates how to use data mining techniques to uncover students' problem-solving processes and highlights what discoveries these techniques provide to enhance educational research.

Generally, there are three popular techniques used to analyze students' process data in game-based learning environments: Bayesian networks (Friedman, Geiger, & Goldszmidt, 1997), logistic functions (Wright, 1995), and deep learning (LeCun, Bengio, & Hinton, 2015). Studies showed that these techniques performed differently when the data features were various (Cui et al., 2019; Hamim, Benabbou, & Sael, 2019). Deep learning overfits smaller datasets but better exploits larger ones. Logistic functions can capture students' long-term information—a main issue of recurrent neural networks (Hochreiter, Bengio, Frasconi, & Schmidhuber, 2001), especially when students' learning interactions are in large numbers. Bayesian networks assume that students' learning processes follow a Markov process, and their latent learning states can be estimated by the observed learning interactions (Arroyo & Woolf, 2005; Corbett & Anderson, 1994). HMM is a directed graph model which can be seen as a specific case of Bayesian networks. It has been widely used in speech recognition and time-series data analyses. In this study, the dataset was smaller than other public datasets, such as *Assistments*, and there was no long-term information in students' learning interactions. Since we can only observe the sequence of students' gameplay actions, and their problem-solving phases are invisible, HMM provides an aggregated interpretation of students' problem-solving phases and the transition probabilities between these phases (Clark et al., 2012; Jeong, Biswas, Johnson, & Howard, 2010).

Table 1 shows the essential components of HMM. It has two simplifying assumptions (Jurafsky & Martin, 2018). First, the previous phase impacts the future phase only via the current one; second, the emission probability of an observation $\boldsymbol{O}_t$ depends only on the phase at t moment. In this study, we assume that students' future problem-solving phase only depends on their current phase, and students' current gameplay action only correlates with their current problem-solving phase.

In ***Zoombinis***, each gameplay action includes hundreds of features, implying the observation sequence is a multidimensional matrix for which a standard HMM is not applicable anymore. The CHMM modeled by Gaussian models is a good solution for multidimensional data analyses (Chen et al., 1995; Matsuyama, 2011; Panahandeh, Mohammadiha, Leijon, & Händel, 2013). While successfully modeling students' multidimensional interactions, CHMM cannot disclose the inherent sequential structure of the gameplay actions. Sequence mining (Dong & Pei, 2007; Kinnebrew & Biswas, 2012; Zaki, 2001) is another competent technique to discover students' strategies manifested over their problem-solving processes (Baker, 2010; Baker & Inventado, 2014), which has been broadly used to explore students' frequent patterns and common behaviors in their learning processes (Kinnebrew, Segedy, & Biswas, 2014). In this study, we first employ CHMM to label students' every attempt as one of the "hidden" problem-solving phases. Sequence mining is then used to identify frequent and key patterns when students transferred from stuck moments to strategic problem-solving. By applying the integrated approaches, this work aims to reveal students' problem-solving processes and strategies employed to support their problem-solving in ***Zoombinis***.

Table 1
Components of HMM (Jurafsky & Martin, 2018).

Components	Descriptions
$S = s_1 s_2 \ldots s_M$	A set of phases.
$\boldsymbol{O} = \boldsymbol{O}_1 \boldsymbol{O}_2 \ldots \boldsymbol{O}_T$	Observation sequence.
$\boldsymbol{A} = A_{11} A_{ij} \ldots A_{MM}$	Transition probabilities, where A_{ij} represents the probability of transferring from phase i to phase j.
$\boldsymbol{B} = b_i(\boldsymbol{O}_t)$	Emission probabilities, representing the probability of an observation $\boldsymbol{O}_t$ being produced by a phase i.
$\boldsymbol{\pi} = \pi_1 \pi_2 \ldots \pi_M$	Initial probabilities.

3. Methodology

3.1. Participants and learning environment

Participants in this study include 30 students (18 males, 12 females) in grades 3–7 with a wide range of cultural backgrounds. These students were recruited from both local schools and after-school programs and had no prior knowledge or experience with ***Zoombinis***. All participants were asked to work on one or more puzzles in ***Zoombinis*** on an individual computer. Playtest sessions last about 1 h without any interference or external interventions. Table 2 is the information of participants.

Zoombinis is designed as a puzzle-based game situated in problems, allowing many scaffolded problem-solving processes for young students (Rowe et al., 2017). It includes 12 puzzles wherein students work through logic problems involving bringing characters to safety by figuring out problems involving sorting, matching, and sequencing attributes of the Zoombinis. To illustrate our methodology, we analyze the gameplay data generated from a specific puzzle called ***Pizza Pass***. This puzzle is situated in ill-structured problems that aim to prepare and motivate students' mathematics concepts essential for computing and programming. This puzzle has different difficulty levels, wherein one or more trolls block the Zoombinis' paths. Each troll requires a pizza with a specific set of toppings. Students have several attempts in each round to find the correct combination of pizza (and ice cream at higher levels) toppings desired by a target troll (see Fig. 1).

3.2. Data source

Zoombinis recorded every action when students interacted with a certain puzzle. Each item in gameplay log data included students' identifier, timestamp, type of actions (e.g., select or deliver) with descriptive features, and other specific information. Completing an attempt means a student successfully created a new combination of toppings with ordered or unordered plans, and the combination of toppings might include some correct or incorrect ones. After delivering each combination (i.e., each attempt), troll's interactions (e.g., accepts, wants more, or rejects) represented the result of this attempt. In this case, we used students' attempts to establish a granularity of students' gameplay actions. Besides, students' first attempts were excluded because they were applied to be familiar with ***Pizza Pass***.

3.3. Data preprocessing

3.3.1. Human labels for different problem-solving phases

Before data analysis, human labels of students' problem-solving phases were built with the agreement in previous study (Rowe et al., 2018). The defined descriptions of each problem-solving phase were summarized in subsection 2.1.

3.3.2. Data wrangling

First, we treated missing attribute values with mean completer and normalized all data before other analyzing processes. Specifically, we informed that other methods of dealing with missing data were equally acceptable. In order to select meaningful properties of students' attempts, we applied minimum redundancy-maximum relevance (mRMR) as our feature selection method. By simultaneously optimizing minimal redundancy and maximal relevance, mRMR can estimate the mutual information in the low dimensional space, which is less expensive and more reliable (Rachburee & Punlumjeak, 2015). Besides, mRMR has fewer restrictions for the data format. Hence, we used mRMR to extract informative features. The selected features were highly correlated with students' problem-solving phases but independent of each other. The minimum set of the informative features selected by mRMR included four (see Table 3): *PP27*, *PP39*, *PP65*, and *PP78*.

3.4. Data analysis

3.4.1. Modeling students' problem-solving phases with CHMM

3.4.1.1. Gaussian mixture model. The multivariate Gaussian distribution function is defined as:

$$g(\boldsymbol{x};\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^d|\boldsymbol{\Sigma}|}}\exp\left[-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^\top\boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right] \tag{1}$$

Table 2
Participants' grades and gender.

Grades	Gender	
	Male	Female
$3^{rd}-5^{th}$ Grade	9	7
$6^{th}-7^{th}$ Grade	9	5

Fig. 1. A screenshot of ***Pizza Pass*** puzzle gameplay.

Table 3
Selected features.

Features	Descriptions
PP27	Number of pizzas/ice creams made since last partial success (attempt).
PP39	Number of futzes ever.
PP65	Total number of toppings used on current pizza.
PP78	Standard deviation time per pizza/ice cream (this attempt).

where $\boldsymbol{x}$ is the multidimensional input (students' attempts), $\boldsymbol{\mu}$ is the mean, and $\boldsymbol{\Sigma}$ is the variance; d is the dimension of input.

Gaussian mixture model is defined as:

$$G(\boldsymbol{x}) = \sum_{k=1}^{K} W_k g(\boldsymbol{x}; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{2}$$

where K is the total number of Gaussian models; W_k is the weight of the i^{th} Gaussian model; $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ are the mean and the variance of the k^{th} Gaussian model. W_k, $\boldsymbol{\mu}_k$, and $\boldsymbol{\Sigma}_k$ are obtained from the Expectation-Maximization algorithm and Maximum Likelihood Estimation, where $\varphi(i,k)$ is treated as an intermediate variable.

$\varphi(i,k)$ is defined as the probability of the i^{th} observation vector (i.e., featured attempt) generated from the k^{th} Gaussian model:

$$\varphi(i,k) = \frac{W_k g(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{k=1}^{K} W_k g(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)} \tag{3}$$

where $\boldsymbol{x}_i$ is the i^{th} observation vector.

Log-likelihood function is defined as:

$$p(\boldsymbol{x}|W_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) = \sum_{i=1}^{N} \ln\left[\sum_{k=1}^{K} W_k g(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)\right] \tag{4}$$

where $p(\boldsymbol{x}|W_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$ is the maximum log-likelihood of all observation vectors $\boldsymbol{x}$ produced by the Gaussian mixture model; N is the total number of observation vectors. W_k, $\boldsymbol{\mu}_k$, and $\boldsymbol{\Sigma}_k$ can be calculated when $p(\boldsymbol{x}|W_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$ converged stably.

3.4.1.2. CHMM. A CHMM is defined as $\lambda = [\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{B}]$. $\boldsymbol{B}$ is a matrix consisting of $b_j(\boldsymbol{O}_t)$, where $b_j(\boldsymbol{O}_t)$ is defined as the probability of a particular observation vector obtained by the j^{th} hidden phase at t moment:

$$b_j(\boldsymbol{O}_t) = \sum_{k=1}^{K} W_{jk} g(\boldsymbol{O}_t; \boldsymbol{\mu}_{jk}, \boldsymbol{\Sigma}_{jk}) = \sum_{k=1}^{K} W_{jk} b_{jk}(\boldsymbol{O}_t) \tag{5}$$

where W_{jk}, $\boldsymbol{\mu}_{jk}$, and $\boldsymbol{\Sigma}_{jk}$ are the weight, the mean, and the variance of the k^{th} Gaussian model when the hidden phase is s_j; $b_{jk}(\boldsymbol{O}_t)$ is the probability of observing a specific vector $\boldsymbol{O}_t$ from the k^{th} Gaussian model under the phase s_j; $g(\boldsymbol{O}_t; \boldsymbol{\mu}_{jk}, \boldsymbol{\Sigma}_{jk})$ is calculated as follows:

$$g(\boldsymbol{O}_t;\boldsymbol{\mu}_{jk},\boldsymbol{\Sigma}_{jk}) = \frac{1}{\sqrt{(2\pi)^d|\boldsymbol{\Sigma}_{jk}|}}\exp\left[-\frac{1}{2}(\boldsymbol{O}_t-\boldsymbol{\mu}_{jk})^\top\boldsymbol{\Sigma}_{jk}^{-1}(\boldsymbol{O}_t-\boldsymbol{\mu}_{jk})\right] \tag{6}$$

3.4.1.3. Establish the model. Set up the initial parameters by random selection:

$$\lambda = [\boldsymbol{\pi},\boldsymbol{A},\boldsymbol{B}] \tag{7}$$

In order to get $\boldsymbol{\pi}$, $\boldsymbol{A}$, $\boldsymbol{W}$, $\boldsymbol{\mu}$, and $\boldsymbol{\Sigma}$, we iteratively employed Baum-Welch algorithm and Maximum Likelihood Estimation (Daniel & James, 2000), while $\zeta_t(h)$ and $\gamma_t(h,j)$ are intermediate variables calculated by the following equations:

$$\zeta_t(h) = \frac{\alpha_t(h)\beta_t(h)}{\sum_{h=1}^{M}\alpha_t(h)\beta_t(h)} \tag{8}$$

$$\gamma_t(h,j) = \frac{\alpha_t(h)a_{hj}b_j(\boldsymbol{O}_{t+1})\beta_{t+1}(j)}{\sum_{h=1}^{M}\sum_{j=1}^{M}\alpha_t(h)a_{hj}b_j(\boldsymbol{O}_{t+1})\beta_{t+1}(j)} \tag{9}$$

where $\zeta_t(h)$ represents the probability of hidden phase is s_h at t moment, $\gamma_t(h,j)$ represents the probability of hidden phase is s_h at t moment and s_j at $t+1$ moment. $\alpha_t(h)$ and $\beta_t(h)$ are the forward probability and backward probability (Daniel & James, 2000) at t moment. $\boldsymbol{M}$ is the total number of hidden phases; a_{hj} is the transition probability from phase s_h to s_j.

Stop when $p(\boldsymbol{O}|\lambda)$ converged stably:

$$p(\boldsymbol{O}|\boldsymbol{\lambda}) = \sum_{h=1}^{M}\alpha_T(h) \tag{10}$$

where $p(\boldsymbol{O}|\lambda)$ is the maximum likelihood of the observation sequences $\boldsymbol{O}$ (a number of students' attempts) produced by a specific model λ; $\alpha_T(h)$ is the forward probability at T moment.

3.4.2. Exploring students' problem-solving patterns with sequence mining

We applied the abbreviation (see Table 4) for all gameplay actions in the following sections.

For a certain attempt, a student may have several select or remove actions to make a new combination of toppings. After delivering this new combination, the troll's feedback indicates whether this combination is correct or not. Based on this interpretation, only select and remove actions contain much meaningful information about how students employ strategies to select toppings and arrange the orders. Therefore, we mainly used students' select and remove actions for sequence mining analysis. To be more precise, we added one label to describe the correctness of each selection. A correct selection represents this topping is one correct dimension of the solution, while an incorrect selection means a false dimension.

We used Python packages to transform the raw data into coded data and then performed the Prefixspan algorithm (Han et al., 2001). The threshold was set up as 0.5, indicating that the results only showed the frequent sequences in more than 50%. We first investigated all attempts (total in 906) generated from 30 students. Since CHMM had labeled all students' attempts as different problem-solving phases, we then explored the frequent patterns in different phases separately. Using the previous literature (Pei, Han, & Wang, 2007) as a guideline, sequence mining in educational research is required to incorporate specific constraints such as the minimum/maximum length of a pattern to obtain educational meanings. Therefore, we specified a constraint for the Prefixspan algorithm with 10 maximum and 3 minimum actions in each pattern. The reason for this constraint is that there are at least three actions (i.e., select, deliver, and troll's interactions) generated by an attempt in ***Pizza Pass***. Besides, non-meaningful patterns or similar patterns were excluded. For example, a super-pattern, *SI* → *SI* → *RM* → *DL* → *DS*, was combined with its sub-pattern, *SI* → *DL* → *DS*. Since these two patterns denote the same strategy that testing one topping at each attempt.

Table 4
Abbreviations for gameplay actions.

Abbreviations	Descriptions
S	*SELECT_PIZZA_TOPPING*
SI	*SELECT_PIZZA_TOPPING* (incorrect)
SC	*SELECT_PIZZA_TOPPING* (correct)
RM	*REMOVE_PIZZA_TOPPING*
DL	*DELIVER_PIZZA_ICE_CREAM*
R	*TROLL_REJECTS_DELIVERY*
DS	*TROLL_DISLIKES_SOMETHING*
WM	*TROLL_WANTS_MORE*
A	*TROLL_ACCEPTS*

4. Results

4.1. How to apply data mining techniques to uncover students' problem-solving processes in **Zoombinis**?

4.1.1. Modeling students' problem-solving phases with CHMM

To label students' problem-solving phases, we calculated and compared the log-likelihood $p(\boldsymbol{O}|\lambda_i)$ of λ_i (λ_T: **Trial and Error**; λ_S: **Systematic Testing**; λ_I: **Implement Solution**; λ_G: **Generalize Solution**). The maximum $p(\boldsymbol{O}|\lambda_i)$ implied this attempt was identified as the corresponding phase *i*. Fig. 2 illustrates the process of identifying students' problem-solving phases with CHMM. 4-fold cross-validation was applied to validate the accuracy of the results. The developed model had 91.11% agreement with human labels, performed ROC/AUC value of 0.7041. Table 5 shows several examples of identification results produced by CHMM.

The initial probabilities and the transition probabilities are shown in the following matrices:

$$\boldsymbol{\pi} = [0.4015 \quad 0.4167 \quad 0.1364 \quad 0.0454] \qquad \boldsymbol{A} = \begin{bmatrix} 0.8136 & 0.1676 & 0.0141 & 0.0047 \\ 0.0299 & 0.6119 & 0.2836 & 0.0746 \\ 0.0645 & 0.0215 & 0.8817 & 0.0323 \\ 0.0385 & 0.1154 & 0.0769 & 0.7692 \end{bmatrix}$$

whereπ_i represents starting from **Trial and Error**, **Systematic Testing**, **Implement Solution**, and **Generalize Solution**, respectively. A_{ij} is the probability of transferring from the i^{th} phase to the j^{th} one.

According to $\boldsymbol{\pi}$, most of these 30 students began with **Trial and Error** ($p = 0.4015$) and **Systematic Testing** ($p = 0.4167$) in their problem-solving processes. The diagonal entries of $\boldsymbol{A}$ suggest that these students had difficulty in progressing to higher problem-solving phases. For example, the probability of looping in **Implement Solution** was 0.8817, whereas transferring to **Generalize Solution** was only 0.0323. At the same time, some students performed successful transitions with efficient strategies and deserved to be investigated further.

Based on Table 5, the transitions between different phases are more likely to occur when their log-likelihoods are closer. For example, a student's problem-solving phases were identified as **Systematic Testing** (the 6^{th} example in Table 5) at t moment and **Implementing Solution** at $t + 1$ moment by human labels. At t moment, the log-likelihoods of λ_s (−2.09) and λ_I (−2.05) were too close to make CHMM generate the correct identification. In other words, despite fact that human labels categorized the attempt as **Systematic Testing**, this student's problem-solving behaviors exhibited a tendency towards **Implement Solution** at t moment. The transition between these two phases was going to happen, and it did at the student's next attempt. As a result, we can estimate how difficult it is for students to propel their problem-solving processes by comparing the log-likelihoods. Moreover, this comparison can be used to capture students' real-time challenges and locate the moments when transitions are about to happen for deeper examination.

4.1.2. Exploring students' problem-solving patterns with sequence mining

To understand students' problem-solving strategies, we applied sequence mining techniques to identify frequent patterns across all attempts and different phases, respectively. There were two measures of pattern frequency in this study: *s*-support is the total number of students who exhibited a frequent pattern in their attempts; *i*-support is the episode frequency, defined as the total number of times a frequent pattern occurred in all attempts.

First, we investigated frequent patterns of all attempts generated by 30 students. Three strategies were identified: testing one topping at each attempt (*Testing one*); adding a new topping at each attempt while keeping what has been tested correctly before (*Additive*); selecting all toppings at one attempt then removing them one by one in the following attempts (*Winnowing*). Table 6 shows the patterns of each strategy.

Testing one ($M = 7.43$, $SD = 3.17$) was the most applied strategy, while *Winnowing* ($M = 3.88$, $SD = 5.86$) was rarely used. The mean of *Winnowing* indicates that students applied it few times despite knowing about this strategy. However, the standard deviation of

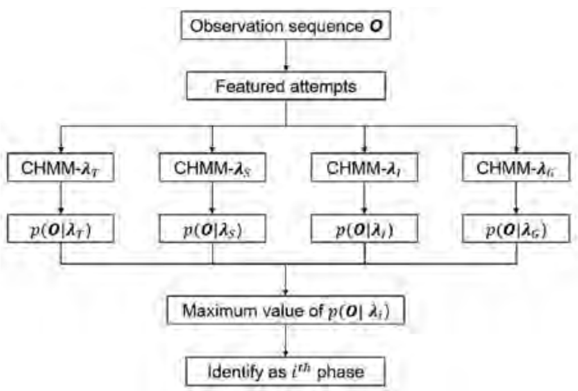

Fig. 2. Diagram of identification process.

Table 5
Examples of the identification results.

i^{th}	Human labels	CHMM	Log-likelihood			
			λ_T	λ_S	λ_I	λ_G
1	Trial and Error	Trial and Error	−3.29	−4.23	−3.48	−8.83
2	Trial and Error	Trial and Error	−3.26	−5.60	−4.46	−12.11
3	Trial and Error	Trial and Error	−3.28	−5.78	−4.60	−12.52
4	Trial and Error	Trial and Error	−3.34	−6.75	−5.34	−14.74
5	Systematic Testing	Systematic Testing	−3.64	−2.19	−2.24	−3.54
6	Systematic Testing	Implement Solution	−3.57	−2.09	−2.05	−3.31
7	Systematic Testing	Implement Solution	−3.52	−2.26	−2.15	−3.78
8	Systematic Testing	Systematic Testing	−3.51	−2.44	−2.67	−4.77
9	Implement Solution	Systematic Testing	−3.44	−1.67	−1.68	−2.52
10	Implement Solution	Implement Solution	−3.40	−1.78	−1.74	−2.84
11	Implement Solution	Implement Solution	−3.30	−2.36	−2.11	−4.37
12	Implement Solution	Implement Solution	−3.30	−2.84	−2.46	−5.51
13	Generalize Solution	Systematic Testing	−3.75	−1.99	−2.07	−2.76
14	Generalize Solution	Generalize Solution	−4.72	−2.28	−2.77	−1.90
15	Generalize Solution	Implement Solution	−3.64	−2.43	−2.33	−3.99
16	Generalize Solution	Implement Solution	−3.51	−3.34	−2.93	−6.37

Table 6
Patterns of three strategies.

Strategy	Frequent Pattern[a]	*s*-support	*i*-support	Mean[b]	SD[c]
Testing one	$S \rightarrow DL \rightarrow S \rightarrow DL$	30	223	7.43	3.17
Additive	$S \rightarrow DL \rightarrow S \rightarrow S \rightarrow DL$	26	181	6.96	4.20
Winnowing	$S \rightarrow S \rightarrow S \rightarrow DL \rightarrow S \rightarrow S$	17	66	3.88	5.86

[a] At least one *S* should be *SC* after the first *DL* in each strategy.
[b] Mean = *i*-support/ *s*-support.
[c] SD denotes standard deviation.

Winnowing is higher than the other two strategies, suggesting this strategy might be practical among a small group. *Additive* was also popular among these 30 students. The mean of *Additive* shows that students used this strategy frequently if they could understand it.

Second, we examined the frequent patterns in different problem-solving phases. This step allows us to determine how students used problem-solving strategies differently and which strategies facilitated effective transitions in different phases. Table 7 shows the results.

In **Trial and Error**, there are three frequent patterns. The first pattern presents the transition trend from random selection ($SI \rightarrow SI \rightarrow DL$) to *Testing one* ($SI \rightarrow DL$). This pattern cannot be considered as *Winnowing* because no correct selection was made. Similarly, even though the third pattern indicates a preliminary concept of *Winnowing*, it should not be mistaken for this strategy because the correct selection is removed at the first delivery.

In **Systematic Testing**, the first pattern includes *Testing one*, the second pattern includes *Winnowing*, and the third pattern includes *Additive*. All patterns except the fourth in this phase show at least one correct selection after the first delivery, indicating that students comprehended and used these strategies efficiently. The fourth pattern, on the other hand, cannot be identified as any strategies because no evidence shows the dependency between two adjacent deliveries.

In **Implement Solution**, the first pattern is recognized as *Winnowing*. This pattern also implies that students have found one correct dimension of the solution. Even though no strategies are used, the second pattern suggests that all dimensions of the solution have been

Table 7
Frequent patterns in different problem-solving phases.

Phase	i^{th}	Pattern	*s*-support
Trial and Error	1	$SI \rightarrow SI \rightarrow DL \rightarrow DS \rightarrow R \rightarrow SI \rightarrow DL$	21
	2	$SI \rightarrow DL \rightarrow DS \rightarrow R \rightarrow SI \rightarrow SI \rightarrow SI \rightarrow DL$	19
	3	$SI \rightarrow SI \rightarrow SC \rightarrow DL \rightarrow DS \rightarrow SI \rightarrow SI \rightarrow DL$	19
Systematic Testing	1	$DS \rightarrow SI \rightarrow DL \rightarrow R \rightarrow SC \rightarrow DL$	23
	2	$R \rightarrow SC \rightarrow SI \rightarrow SI \rightarrow DL \rightarrow SC \rightarrow SI \rightarrow DL$	16
	3	$SC \rightarrow DL \rightarrow DS \rightarrow R \rightarrow SI \rightarrow SC \rightarrow DL$	16
	4	$DS \rightarrow R \rightarrow SC \rightarrow SI \rightarrow SC \rightarrow RM \rightarrow DL$	16
Implement Solution	1	$SC \rightarrow SI \rightarrow DL \rightarrow DS \rightarrow SC \rightarrow DL \rightarrow WM$	17
	2	$DL \rightarrow DS \rightarrow SC \rightarrow SC \rightarrow SC \rightarrow DL \rightarrow A$	17
Generalize Solution	1	$A \rightarrow SC \rightarrow DL \rightarrow WM \rightarrow SC \rightarrow SC \rightarrow DL \rightarrow A$	18
	2	$A \rightarrow SC \rightarrow SC \rightarrow SI \rightarrow DL \rightarrow SC \rightarrow SC \rightarrow DL \rightarrow A$	16

identified. One possible explanation is that students might use various strategies before the first delivery in the second pattern, so it is difficult to identify the most frequent one before the first delivery.

In **Generalize Solution**, the first pattern represents *Additive*, whereas the second one includes *Winnowing*. These two patterns illustrate that students used strategies effectively and were able to solve the problems. Two (or more) consecutive acceptances from trolls is a distinct attribute of the patterns in **Generalize Solution**. Students could generalize the problem-solving strategies for their strategic analysis when confronted with new problems.

*4.2. How do students advance their problem-solving processes in **Zoombinis**?*

To uncover how these 30 students advanced their problem-solving processes in ***Pizza Pass***, we developed a graph that included all gameplay sequences from lower phases to higher ones and calculated the probabilities of all transitions between these sequences. Since we are primarily interested in what are the possible trajectories for these students to solve problems and which strategies efficiently support their transitions, all retrograde paths (students regressed from a higher phase to a lower one) were excluded.

Fig. 3 depicts students' problem-solving processes in ***Pizza Pass***. The nodes represent frequent patterns in different problem-solving phases, and the solid lines between nodes are the transition probabilities. Particularly, pattern_i denotes the i^{th} pattern of each phase (see Table 7). We used the abbreviation "non_fre_pattern" to represent all infrequent patterns which were not identified by sequence mining techniques.

According to Fig. 3, the most possible path from **Trial and Error** to **Generalize Solution** for these 30 students is: **Trial and Error**_pattern_1 → **Systematic Testing**_pattern_1 → **Implement Solution**_pattern_1 → **Generalize Solution**_pattern_1, with the transition probabilities of 0.25, 0.32, and 0.98, respectively. The transitions from **Trial and Error**_pattern_2 to **Systematic Testing**_pattern_3 ($p = 0.02$), from **Systematic Testing**_pattern_3 to **Implement Solution**_pattern_1 ($p = 0.14$), and from **Implement Solution**_pattern_2 to **Generalize Solution**_pattern_1 ($p = 0.02$) obtain lower probabilities compared with other transition sequences (not included infrequent patterns). Besides, not all transitions are continuous. For example, students could skip **Systematic Testing** and transferred from **Trial and Error**_pattern_3 to **Implement Solution**_pattern_1 directly, even though the probability was only 0.08. Jumping from **Systematic Testing**_pattern_1 to **Generalize Solution**_pattern_1 was also possible, and its probability was 0.23. In addition, no transitions have been found from **Systematic Testing**_pattern_2 or **Systematic Testing**_pattern_4 to any patterns of higher phases, indicating that if students went into these two patterns of **Systematic Testing**, they might be stuck in their problem-solving processes and could not find solutions.

We then explored the sum of probabilities and addressed other important findings. Students who were able to transfer from **Trial and Error** to **Systematic Testing** had a great chance ($p = 0.61$) of transferring to **Systematic Testing**_pattern_1, regardless of which patterns they used in **Trial and Error**. Moreover, the probability of transitions from any lower phases to **Implement Solution**_pattern_1 was 0.54. These two probabilities suggest that *Testing one* and *Winnowing* were critical for students to advance their

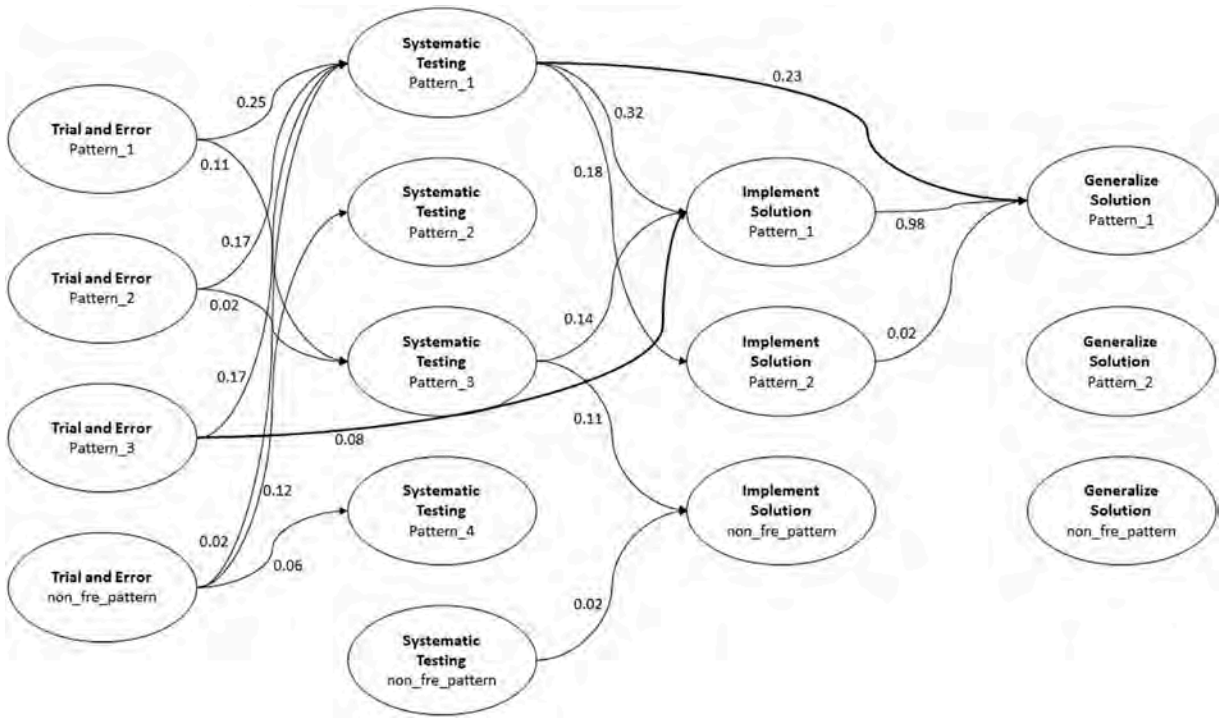

Fig. 3. Students' problem-solving processes in ***Pizza Pass***.

problem-solving processes. On the other hand, no transitions were made from any lower phases to **Generalize Solution**_pattern_2, which implies that *Additive* played the more important role when students generalized their solutions. By counting the possible paths of transitions, we found that the infrequent patterns in **Trial and Error** included three paths toward **Systematic Testing**, with the total probability of 0.20. There were also three paths from **Systematic Testing**_pattern_1 to the higher problem-solving phases, and the total probability was 0.73.

5. Discussion

This research aims to integrate data mining techniques to uncover how students advance their problem-solving processes in ***Zoombinis***. Data mining approaches were used to deal with multidimensional log data to build a scalable and reliable model that depicts students' problem-solving processes in the specific puzzle, ***Pizza Pass***. The results revealed students' problem-solving trajectories and efficient strategies they used in certain phases. This study was inspired by previous work (Rowe et al., 2017) which used video recordings and classification techniques to examine students' problem-solving behaviors. By employing integrated data mining approaches, we extended the prior research to interpret how, when, and why students advanced their problem-solving processes. The following subsections discuss the results with respect to our research questions.

5.1. *How to apply data mining techniques to uncover students' problem-solving processes in **Zoombinis**?*

Many current analyses of students' problem-solving processes by data mining approaches are laden with algorithm developments. Zhou, Xu, Nesbit, and Winne (2010) suggested that empirical educational data mining should incorporate research contexts and domain knowledge. In an effort to mitigate these barriers, we developed an integrated method to explore students' gameplay actions—problem-solving that can be demonstrated through behaviors within the game-based learning itself (Rowe, Asbell-Clarke, & Baker, 2015). CHMM is a robust evidence-modeling approach for analyzing multidimensional observation sequences. By examining the transition probabilities and comparing the log-likelihoods, CHMM helps us infer how difficult the transitions occurred between two corresponding phases and address students' struggling moments that required further interventions. From another perspective, concerning the role of gameplay actions in representing trajectories of students' problem-solving, much granular evidence about students' problem-solving performance is overlooked if we only employ CHMM. Analyzing students' gameplay patterns with sequence mining techniques provides a fine-grained examination of what strategies they used to overcome the stuck moments in different phases. Leveraging the combination of CHMM and sequence mining enables us to automatically trace students' problem-solving processes in ***Zoombinis***. Such results can be used to analyze students' problem-solving trajectories and scaffold students' challenging moments.

While earlier work (Rowe et al., 2017) manually labeled students' problem-solving phases and strategies in ***Zoombinis***, it lacked the ability to explain how students used strategies and why transitions to higher phases occurred. In most game-based learning environments, students' knowledge construction processes are implicit and self-controlled. Traditional assessments, such interviews and quizzes, fail to take account of students' knowledge construction processes. By viewing students' problem-solving as phase-based processes, CHMM and sequence mining examine their in-process adversity and prosperity. The results suggest that it is promising to deploy these data mining techniques at scale and in real-time to capture students' covert problem-solving processes. Contributing to the growing literature in using data mining approaches to track students' game-based learning processes, this study allows researchers to establish higher-level inferences about students' problem-solving processes (Baker, 2010). For example, when students fall into the traps of games? When students have "slipped"? And when students engage in efficient problem-solving? Following the conceptual framework proposed by Rowe et al. (2017), we improve the implications of data mining approaches in interpreting and modeling the sophistication of students' problem-solving processes, and further improve students' personalized learning experience in game-based learning environments.

One primary concern of this integrated method is that gameplay log data cannot include external information when students have off-computer behaviors. Due to the variety of possibilities in authentic learning environments, students may seek help or discuss with their peers to solve problems (Price, Liu, Catété, & Barnes, 2017). Given this limitation, future work should focus on using multimodal data such as facial expressions and eye movements to identify students' problem-solving processes. Besides, students' current problem-solving phase is solely reliant on the previous one due to the assumptions of HMM. It is limited because students' current problem-solving phase must be influenced by their previous experience in real game-based learning situations. Evaluating the effects of earlier phases on students' subsequent problem-solving phases is still a crucial issue that should be considered in future research.

5.2. *How do students advance their problem-solving processes in **Zoombinis**?*

According to the results, the majority of these 30 students were inclined to loop in a certain problem-solving phase, especially in **Trial and Error**. As Lönnberg, Berglund, and Malmi (2009) proposed, inevitable trials provided the opportunities to fully comprehend the underlying rules of problems. Even though game principles may mask theoretical understanding for some students in **Trial and Error**, random attempts allow students to construct conceptual and procedural knowledge and further enhance their problem-solving performance. Fig. 3 shows that using problem-solving strategies is essential for efficient transitions in students' problem-solving processes. Three useful strategies (see Table 6) of all gameplay actions and eleven frequent patterns (see Table 7) in different phases were identified by sequence mining techniques. The findings are consistent with previous literature (Joo & Kim, 2015), which argued that problem-solving strategies mediated the relationship between metacognition and achievement. It requires organized cognitive skills to establish logic and algorithmic plan for the target problem (Zhao et al., 2019). In this study, using *Testing one* was a hallmark that students started their systematic problem-solving, while *Winnowing* effectively bridged the gaps between **Systematic Testing** and **Implement Solution**. When students transferred to **Generalize Solution**, they migrated the strategies and solutions to other problems, where *Additive* was the key to achieve this goal.

In games, students' problem-solving processes are difficult to identify because their knowledge acquisition processes are implicit (Silva, Macedo, Teixeira, Lanzer, & Graziani, 2017). All we have are students' self-paced gameplay actions. Previous studies (Liu, Lee, Kang, & Liu, 2016; Sawyer et al., 2018) have examined students' problem-solving behaviors by considering the gameplay duration and grades. However, these features cannot satisfy the tasks that aim to measure students' in-process performance. This study captures students' real-time problem-solving phases and discovers frequent patterns within each phase, which can be used to assess students' problem-solving achievement in learning games. Game designers and instructors may respond differently based on students' knowledge mastery and learning performance. On the one hand, when students have some challenges to design useful rules to escape from loops in lower phases, appropriate interventions and adaptations should be provided to support students' zone of proximal development (Cole, John-Steiner, Scribner, & Souberman, 1978). On the other hand, strategic and ordered patterns identified in higher phases can be viewed as convincing evidence to measure students' problem-solving abilities and skills such as dimensions, sorting, and comparing. As instructors and educators become more interested in evaluating students' problem-solving processes in learning games, this study shows the promise to trace and analyze students' problem-solving practices stealthily and efficiently. Designing appropriate interventions and learning protocols in accordance with students' in-process gameplay actions is vital to promote personalized problem-solving skill acquisition in game-based learning environments.

Even so, we faced some limitations in our work. First, the sample size is small. Therefore, we simply illustrated how to employ the integrated data mining techniques to uncover students' problem-solving processes in ***Zoombinis***. More work should be done to examine diverse students' problem-solving processes at scale and obtain general findings. Second, infrequent patterns showed in students' transitions between problem-solving phases are not thoroughly investigated. Since game-based learning allows students to approach their solutions in a variety of paths, a preliminary examination of students' problem-solving strategies in this small sample is insufficient to generalize. Following that, studies should be conducted to identify and examine more strategies. Finally, prior research argued that trace (i.e., gameplay logs) data should be triangulated with self-reported data (Emerson et al., 2020; Syal & Nietfeld, 2020) to improve the evaluation of students' problem-solving processes. Further research avenues may consider incorporating both object and subject perspectives to depict students' problem-solving processes in game-based learning environments.

6. Conclusion

Game-based learning has emerged as powerful and effective context for nurturing students' problem-solving skills (Kailani, Newton, & Pedersen, 2019). The integrated data mining approaches enable a new genre of behaviors analysis that reveals how students implicitly solve problems rather than just summarizing what they exhibit or perform in games. Uncovering students' problem-solving processes with data mining techniques shows the potential to explore "under the hood" at what students demonstrate through gameplay actions which may reflect cognitive strengths that go unnoticed when relying on traditional assessment methods (Nguyen, Gardner, & Sheridan, 2018). Developing and validating efficient methods to investigate students' problem-solving processes that reach a broad range of students and in real-time is just a nascent field of future research.

Ethical considerations

All data was collected and analyzed after approval by the Institutional Review Board. There is no conflict of interest resulting from the research work in this study.

Credit author statement

Tongxi Liu: Conceptualization, Methodology, Formal analysis, Visualization, Software, Writing – original draft, Writing -review & editing. Maya Israel: Writing – original draft, Writing -review & editing, Supervision, Funding acquisition, Project administration, Validation.

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