Feng, X., & Yamada, M. (2021). An Analytical Approach for Detecting and Explaining the Learning Path Patterns of an Informal Learning Game. *Educational Technology & Society*, *24* (1), 176-190.

An Analytical Approach for Detecting and Explaining the Learning Path Patterns of an Informal Learning Game

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ABSTRACT: It is challenging to utilize learning analytic technologies to examine gameplay log data for game-embedded assessment in the field of game-based learning. Analytical approaches based on a new perspective focusing on complicated contextual data are imperative in the current scenario. A relatively new concept called precision education, which focuses on individual learning and provides personalized and timely intervention to different learners, can be regarded as a new perspective for game-based learning. Additionally, the order of knowledge acquisition in the learning environment is a kind of learning path extracted from the contextual information of in-game behavior logs. Therefore, in this study, the authors propose a new analytical approach to identify learning path patterns and elucidate the features of these patterns for an educational game they developed. The statistical analysis shows that learners with diverse learning path patterns have different learning effects, suggesting that the learning path is an important factor in precision education. The practice of using the explanation method to examine the proposed approach can help us understand learners' knowledge acquisition and provide evidence for enhancing the accuracy of precision education and improving the quality of the educational game. The findings are expected to contribute to both game-based learning and precision education.

Keywords: Learning analytics, Game-based learning, Learning path, Informal learning, Precision education

1. Introduction

Game-embedded assessment has become the mainstream method for evaluating game-based learning. This approach assesses learners' performance by tracing and analyzing behavioral process data (Shute, 2011). It is challenging to develop game-embedded assessment utilizing methods of data science such as learning analytics. Although this topic has been studied for nearly 10 years, analytics based on new perspectives is imperative to make the assessment more effective (Kim & Ifenthaler, 2019). Precision education, which is a relatively new concept that focuses on providing an individualized learning experience and timely intervention in learning environments (Hart, 2016), can be considered a new perspective for game-based assessment. Meanwhile, the learning path with regard to learning content might be an influential factor in precision education and can be considered a new analyzed data type in game-embedded assessment. Accordingly, in this study, we propose an analytical approach with regard to the learning path patterns of an informal learning game from the perspective of precision education. The findings are expected to contribute to both game-based learning and precision education.

1.1. Game-embedded assessment for informal learning games

Although digital games are considered a form of entertainment, several studies have shown that these games have the capability to increase intrinsic learning motivation or support cognitive process (Klein & Freitag, 1991). Further, cognitive and learning scientists claim that certain features of the games, such as high interactivity and the provision of immediate feedback, can also aid effective learning environments (Shute & Ke, 2012). Therefore, digital games are considered to have the potential to become attractive and effective learning environments. This approach of using digital games to build learning environments is called "digital game-based learning" (DGBL). Additionally, the assessment of learning effects in game-based learning environments is an important factor in the field of DGBL. However, this factor cannot be comprehended easily, because learners' interactions in games are often variable and complicated, making the evaluation of performance difficult. Since playing games has a strong trait of spontaneity, many educational games have been developed for informal learning (Ke, 2016), which suggests that learning is the result of outside-of-school activities with spontaneity and less rigid curricula (Werquin, 2007). In these cases, there are no observers of learning activities. External assessments such as pre- and post- tests are feasible, but information about behavioral data at the process level is lacking. In such a situation, the learning activity becomes a "black box," and the ability to understand how players learn from the game, explain experimental results, and utilize the results of assessments to improve learning environments is limited (Loh, 2011).

To address the problem of assessment in such contexts, an approach called “game-embedded assessment” has been proposed that seeks to assess a learner’s performance by tracing and analyzing behavioral process data. Since process log data can be collected stealthily even if learning activities occur in an environment without any educator observer, concerns that “learning is a black box” can be avoided (Shute, 2011). Owing to the advantages of game-embedded assessment, it has been considered the mainstream method. However, given the complexity of in-game interaction, it is challenging to analyze the collected log data to realize an effective game-embedded assessment. For the analysis, data science and technology are usually needed, and learning analytics (LA) is considered relevant since it involves “using various data such as logs about learning to clarify education and learning environment improvement” (Ifenthaler, 2015). The in-game log data analysis method has been studied for nearly 10 years, with the research framework developed from traditional evidence-centered design to the application of LA technologies (Kim & Ifenthaler, 2019). As for recent researches, Akram et al. (2018) proposed an analytical framework based on the long short-term memory network to build an automatic game-embedded assessment. Furthermore, Henderson et al. (2020) generated a hybrid data-driven approach by using multiple technologies to assess learners more accurately. In our prior studies, we proposed approaches to clustering learners to identify and visualize the in-game tools using patterns in an educational game we developed (Feng & Yamada, 2019; Feng & Yamada, 2020). Alonso-Fernandez et al. (2019) indicated that under game-based assessment research, an analytics based on new perspectives and a focus on more complex contextual data is needed for assessments to effectively evaluate learners’ performances and provide evidence to improve the quality of educational games.

1.2. Learning paths and precision education

“Precision education” is a relatively new concept and is considered a challenging subject in the field of LA, especially with regard to artificial intelligence (AI) technology (Yang, 2019). The concept of precision education is based on personalized education. Its rationale is similar to precision medicine, which is meant to improve the precision, accuracy, and quality of treatment and disease prevention through an analysis of individual factors. Therefore, the goal of precision education is to apply LA technologies to individual learning factors, such as learning patterns or strategies, to identify and evaluate learning activities and effects, including identifying students who may be at risk of developing a learning disability, so as to provide them timely personalized educational intervention (Hart, 2016). For example, Tsai et al. (2020) used a statistical and an AI method (deep neural networks) to estimate students’ probability of dropping out of university, and this approach was employed to identify the students expected to drop out and need timely interventions. Additionally, research examining possible influential factors can contribute to precision education. For example, Lu et al. (2018) examined 21 variables in a blended learning environment, and subsequently identified seven factors that can predict students’ performance when only one-third of the semester has elapsed. This new concept has the potential to provide a new perspective for analytics in game-embedded assessment. Specifically, games are often open-ended, so players have personalized learning experiences. This feature shows the feasibility and suitability of integrating game-embedded assessment with precision education.

As for the objective being analyzed, we believe that the learning path is a piece of information that can be analyzed to create a personalized precision education experience. The learning path term generally refers to the route from preconception to the target, and usually includes the order in which the content is learned. Learning paths are considered one of the individual attributes of learning behavior and may influence learning effects (Williams & Rosenbaum, 2004; Shou et al., 2020). In an open-ended learning environment such as games or the e-learning system, the control over interactions within the learning environment shifts from the educator to the learner, so the learning paths of each individual learner vary. Accordingly, learning paths are a factor that might be analyzed in precision education. There are research studies on learning paths focusing on developing individual optimal learning path predictions and recommendation systems (Su, 2017; Shou et al., 2020), which seem to align with the precision education’s goal, although there is no mention of precision education. For the game-embedded assessment, the learning path with regard to content is also a new data type that should be analyzed. As mentioned earlier, analysis focusing on context information is imperative, and the learning material related to in-game interaction is one form of context data constituting the learning path as well. Since research on learning content arrangement and instructional presentation is rare, despite Ruipérez-Valiente et al. (2019) proposing a visualization approach showing the path of completing tasks in the game, it is considered that the results can only provide insight into students’ behaviors, and the teachers cannot assess the performance directly.

Based on the aforementioned discussion, we believe that exploring an analytical approach to identify learning path patterns and examining the relationship between them and the learning effects is expected to offset the limitations in game-based assessment research and aid precision education. Additionally, given that an understanding of the analysis results, for example explaining the identified patterns, is very important for understanding students' behaviors and improving precision education, an explanatory approach is also needed (Ke, 2016). Three research questions have been proposed below:

- Can the learning path detection approach we propose determine learning path patterns effectively?
- Do learners with diverse detected learning path patterns have different learning results? The answer will reveal whether the learning path can be an influential factor of learning and serve as an important variable in the precision education system.
- Can the explanatory approach proposed in this paper describe the identified pattern functionally to help us understand learners' behavior and promote the accuracy of precision education?

2. The educational game *Hist Maker*

2.1. General introduction

Hist Maker is an educational game developed by us for use in our research. The platforms for the game are PCs with a Windows OS and smartphones with an Android OS. Players can download the game online and play it where and when they wish, allowing them to learn in informal situations. It is a puzzle game intended to help players learn historical concepts related to world civilizations while solving a puzzle. The interfaces are shown in Figure 1.

Figure 1. Initial interface and gameplay interface of *Hist Maker*

There are three major components in the game:

- Core gameplay based on concept maps. Concept maps are considered effective cognitive tools (Novak & Cañas, 2008). The puzzles in the game were designed as concept maps of historical knowledge, which learners can explore while interacting with the game. The gameplay reflects the game characteristics of having a rich interactivity, which is considered to make the learning environment effective and motivational according to game-based learning theories (Shute & Ke, 2012). Also, this game is expected to impart knowledge about not only history, but also other subjects, such as biology and chemistry, that can be presented in the form of concept maps. The potential of generalization is a strength of Hist Maker, and the analytical approaches in our studies could have a broader scope. The core gameplay is closely related to the learning path of content acquisition, which we will discuss in the following sections.
- In-game tools. Based on game-based learning theories about how to make an educational game effective, some support tools were developed for the game. These tools include a task system, a hint tool, and a knowledge repository tool. The task system can provide clear goals to players and make the game an effective goal-oriented learning environment. The hint tool can lower the difficulty of tasks when players find it challenging, in order to provide challenges at the proper level (Gee, 2003), and the knowledge repository tool can work as a cognitive tool to reduce the memory load required when playing games (Bera & Liu, 2006).
- Data collection system. We developed a game-embedded system to help us collect data. An introduction to it along with its details is included in the section "4.3. Data Collection."

2.2. Core gameplay based on concept maps

The core gameplay of Hist Maker is based on concept maps, which are considered an effective cognitive tool for imparting knowledge (Novak & Cañas, 2008). Concept maps are not shown in the game because Charsky and Ressler (2011) pointed out that showing a complex concept map at the beginning of the learning process may diminish learning motivation. The knowledge in concept maps is presented as "elements and formulas" in the puzzle. Each "element" represents a piece of knowledge or concept from history. When learners start a level in the game, there are only a few elements, but they can add new ones by combining two elements that have already been acquired. This format can be described using the formula: "element A + element B = element C." The relationships in concept maps are also represented in this way, and the instructional text is shown when a formula is revealed. For example, for the formula "east of Yellow River Basin + Tribe = Dongyi Tribes," the instructional text is "The Dongyi Tribes were the tribes located east of the Yellow River Basin." Figures 2 and 3 show the correspondence between the concept map and the formulas.

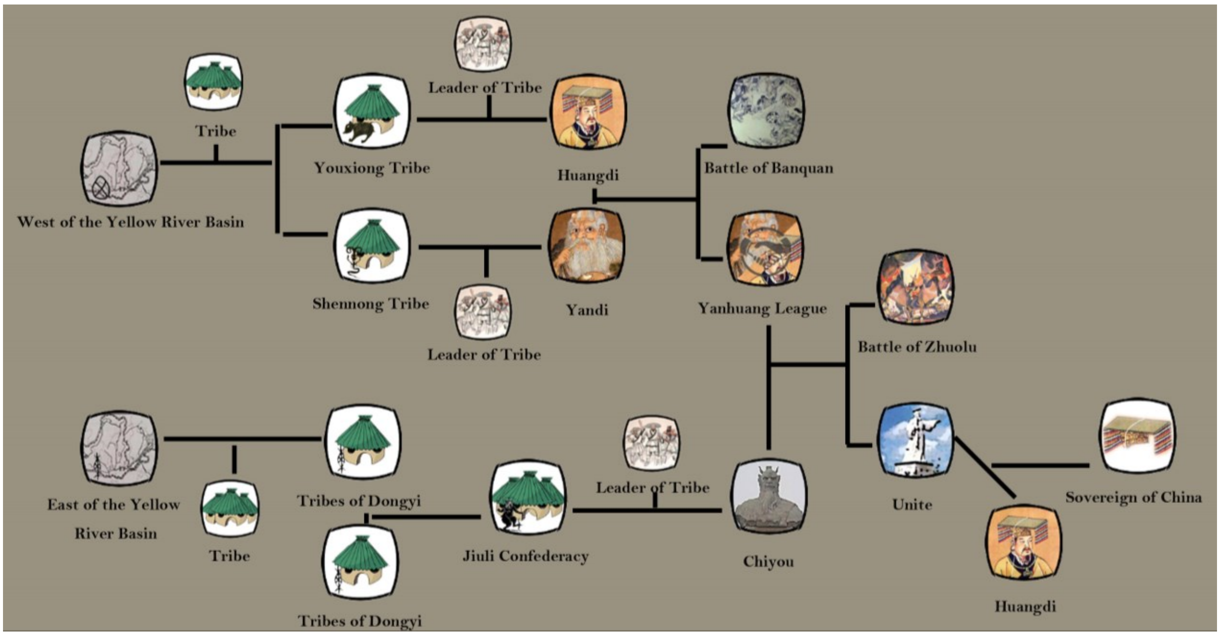

Figure 2. Part of a concept map in the level "The Five Sovereigns era"

In this way, players can explore the content in concept maps using multiple learning paths that involve combining the elements in various orders. Further, since concept maps emphasize the relationship between prior and new knowledge, the order of content acquisition from concept maps may be especially influential on learning effects (Chen, 2009). Therefore, detecting learning path patterns and modifying the design of the formula to eliminate the patterns that lead to negative learning effects is important.

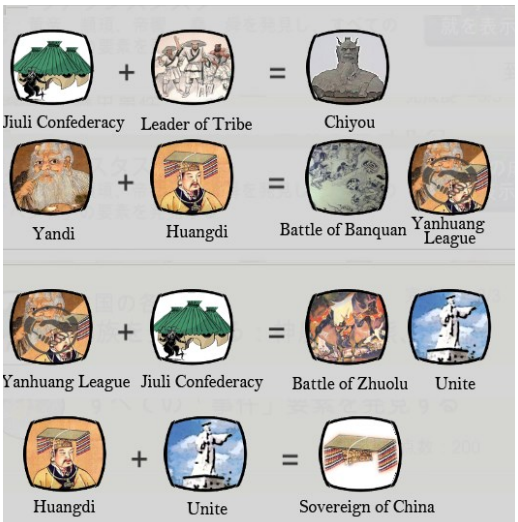

Figure 3. Examples of some of the formulas from the concept map

3. Analytical approach

To detect learning path patterns, the sequential characteristics of learners' content acquisition routes should be described objectively, and a method for grouping learning paths according to their common features is needed. In this study, we used the Levenshtein distance to demonstrate the sequential similarities between routes and then classify the learning sequences using hierarchical cluster analysis. The proposed analytical approach combines the Levenshtein distance and hierarchical cluster analysis.

3.1. The Levenshtein distance

The Levenshtein distance is a measure of distance proposed by the Soviet mathematician Vladimir Levenshtein to show the similarities between two character-strings, such that the higher the degree of similarity between two strings, the shorter the Levenshtein distance. This term refers to the minimum number of editing steps required to transform one character-string into another; thus, it is also termed the "edit distance." Edit operations include inserting, deleting, or replacing a character (Levenshtein, 1966).

The Levenshtein distance is widely used to demonstrate the degree of difference between words, sentences, or essays (e.g., Schepens, 2012). Moreover, the Levenshtein distance can be used with other types of sequential data, including learning paths. For example, Hao et al. (2015) used the Levenshtein distance to propose an approach to analyzing process data from game-based learning tasks. The idea behind the approach is to code each type of action into a single character so that the action sequences in the learning process can be transformed into character-strings. The Levenshtein distance can then be used to represent the distance between the learning sequences of players. In this vein, the Levenshtein distance can also be used to demonstrate the sequential character of the path of content acquisition. However, the approach of Hao et al. (2015) is only available for a learning environment that includes the best action sequence. Additionally, sequences of learning content have not been considered in their study. Our research proposes an original method based on Hao et al. (2015)'s approach to detect learning content path patterns.

3.2. Hierarchical cluster analysis

Cluster analysis is a proper means of detecting "patterns" in a situation in which a clear classification criterion is lacking. The procedure of cluster analysis involves grouping samples based on the distances between them. Samples close to each other are automatically classified as a group (cluster). Samples in the same cluster share common features because short distances represent similarity; these common features can be regarded as the profile of a "pattern." Therefore, when distances indicate the characteristics of players' behaviours and routes of content acquisition, cluster analysis can be used to detect learning path patterns.

To detect learning path patterns, we used hierarchical cluster analysis, which is a way to construct clusters in a hierarchical order. The algorithm is as follows: each sample belongs to a cluster that contains only itself at the beginning; then, the pairs of clusters with the shortest distances are merged into higher-level clusters, and this merging operation is repeated until a specified number of higher-level clusters remains. The merits of hierarchical cluster analysis make it especially well-suited for our research. According to Alonso-Fernandez's (2019) review, clustering is a relatively popular approach for game-based learning research utilizing data science. Although there are various types of cluster analysis, we chose the hierarchical cluster analysis on account of two main merits: One is that the process of clustering can be visualized in the form of a dendrogram, and the other is that it has wide applicability and can be applied to various types of distances. The first merit can help us to determine the final number of clusters based on the resulting merging dendrogram. The second merit is that the algorithm is guaranteed be suitable for dealing with the Levenshtein distance. An example of the application of hierarchical cluster analysis to character-strings is shown in Figure 4.

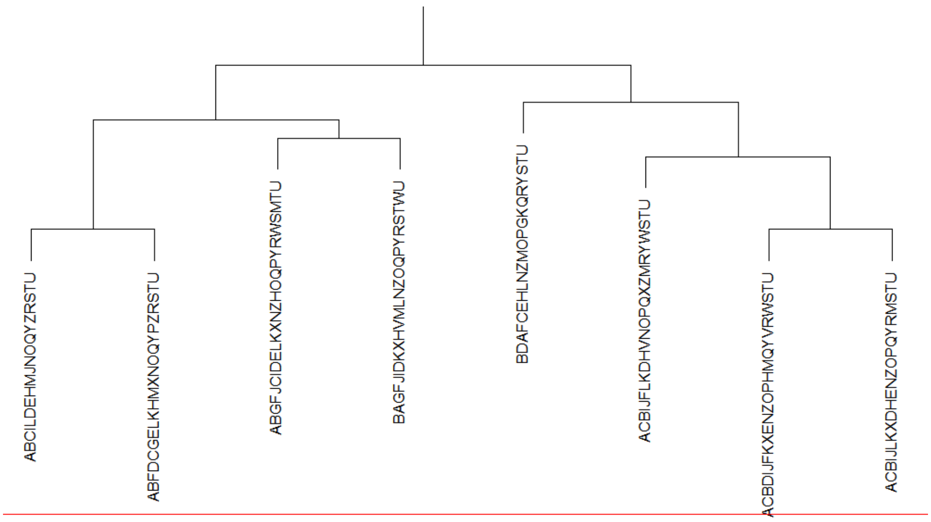

Figure 4. Example of a merging dendrogram of hierarchical cluster analysis

3.3. Analytical approach of this study

Based on the definitions of the terms "Levenshtein distance" and "hierarchical cluster analysis," the analytical approach we propose in this study will be illustrated in this section.

As mentioned above, learners primarily acquire knowledge from instructional texts when attempting to identify the "formulas" in a level. Therefore, the order of actions taken to identify formulas while completing a level is considered the learning path of content, and the learning pattern can be detected from an analysis of the data. Concretely, the analytical approach has four steps:

- Step 1, coding the data. This step is based on the idea that various types of sequential data can be converted into character-strings by coding each piece of single-item data as a unique character. Thus, the first step is to code each formula as a letter of the alphabet so that the learning acquisition path of each learner can be transformed into a character-string.
- Step 2, calculating the Levenshtein distance. Since character-strings can be obtained through Step 1, the Levenshtein distance can be calculated, and the distance can be used to represent the sequential characteristics and the similarities between the learning paths of learners.
- Step 3, implementing a hierarchical cluster. Based on the calculated Levenshtein distance, a hierarchical cluster analysis can be used to classify learners into several clusters. Learners in the same cluster demonstrate common features in their learning path patterns, meaning that each cluster represents a pattern.
- Step 4, explaining the results. To draw educationally meaningful conclusions, the relationships between these patterns and learning effects or gameplay times, as well as the specific features of each cluster, should be discussed. Therefore, the correlations should be examined using statistical methods, and the pattern of each cluster must be presented and explained.

4. Methods

4.1. Participants

To guarantee the randomness of the informal learning behaviors, players were not intentionally recruited. The players played the game and submitted the data completely spontaneously. The data collection was limited to the level “Chinese history: The Five Sovereigns era” in the game, and the participants were all Chinese.

Consequently, we collected valid data from 548 players, and the distribution patterns with regard to their gender and educational status are shown in Figure 5: 423 were male, 110 were female, and 15 failed to indicate their gender. Regarding the educational background, 127 were primary school students, 143 were middle school, 85 were high school students, 110 were university or graduate students, 66 were “other,” including those who worked, and 17 players failed to specify their educational status. These proportions seemed unbalanced, especially for gender, but it is also proof that players chose the game spontaneously. Moreover, the average age is 16.73 (*SD* = 5.38), but 58 players did not answer this question or gave an apparently false answer such as 100 years old.

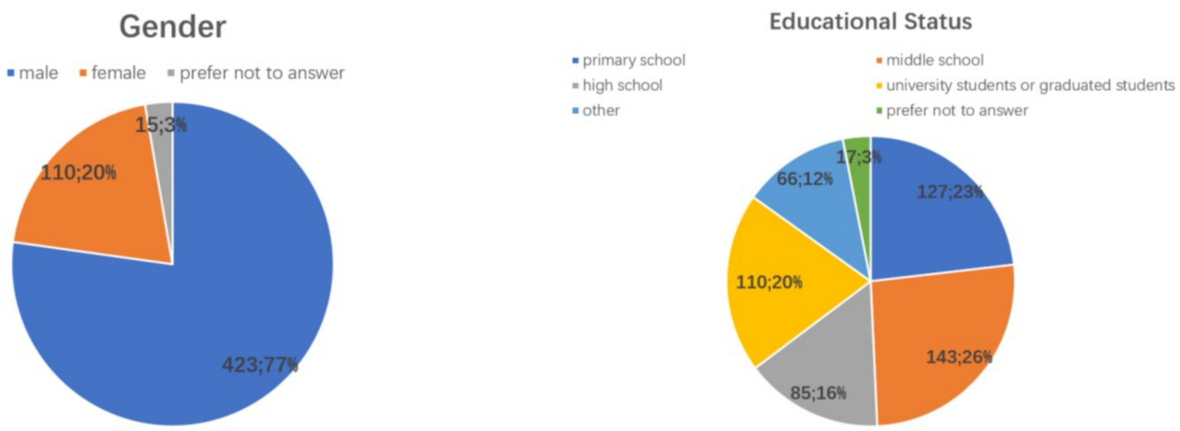

Figure 5. Distribution patterns of learners’ gender and educational status

4.2. Learning game content

In this study, we limited our data collection and analysis to the level “Chinese history: The Five Sovereigns era.” The content of this stage pertained to the “Legendary Era” of prehistoric China before the Xia Dynasty. The reason we chose this era is that our plan of setting the game stages is to show the development of civilizations in chronological order, and the Five Sovereigns era is the first era in Chinese history. Although it is a prehistorical era without adequate archaeological evidence, this period is considered historical because of literary evidence and is included as content in formal history textbooks. Analyzing students’ behaviors in this stage may help us design the stages about follow-up eras with better quality. The content presented in the level included a historical story from the *Records of the Grand Historian* (*Shiji*) of Sima Qian, which is considered the most well-known piece of historical literature about ancient China and is highly authoritative. To provide a flexible, informal learning environment, we decided not to include a time limit for game play, and the players did not need to explore all the formulas. Clearing a level indicated that most of the important knowledge in it had been learned before taking the post-test.

Specifically, the content of the levels was divided into four categories: The main and secondary parts of the pre-unification era, and the main and the secondary parts of the post-unification era. The boundary between the pre- and the post-unification eras is taken as the event when Huangdi defeated the other tribes and unified China area. The main part refers to the knowledge of historical figures and important events in the era, while the secondary parts mostly included information about the activities of historical figures and their contribution to society. Since the analysis required the formulae from this stage to be coded into alphabetical characteristics, a part of the correspondence table is shown in Table 1.

Table 1. Part of the correspondence table of formulae and alphabetical codes

Formula	Alphabetical Code
Tribe+Yellow River Basin West = Tribe Youxiong+Tribe Shennong	A
Tribe+Yellow River Basin East = Tribes in Dongyi	B
Tribe Youxiong+Tribe Shennong = Battle of Banquan+Confederacy of tribes Yanhuang	C
…	…
Nature+Yandi = Agriculture	K
Nature+Huangdi = Calendar	L
Nature+Chiyou = Bronze weapon	M
Huangdi+Unifying China = Sovereign of China	N
Son generation+Huangdi = Shaohao	O
Shaohao+Tribes in Dongyi = Feng Totem	P
Shaohao+Son generation = Zhuanxu	Q
Zhuanxu+Son generation = Diku	R
Diku+Son generation = Yao	S
Yao+Sovereign of China = Demising	T
Yao+Demising = Shun	U
…	…
Huangdi+Sovereign of China = Long Totem	Z

4.3. Data collection

The data collection system embedded in the game was developed for both pre/post-test and game-embedded assessment. The database structure of the game is shown in Figure 6. The players had to complete the pre-test before beginning the game; subsequently, the operation log data were recorded during gameplay, and in the end, when players cleared a level, they completed the post-test and sent us the data on the test answers and operation log. We did not utilize database software such as MySQL, and the collected data are saved in the local storage of the device in *.csv format and sent to us by email.

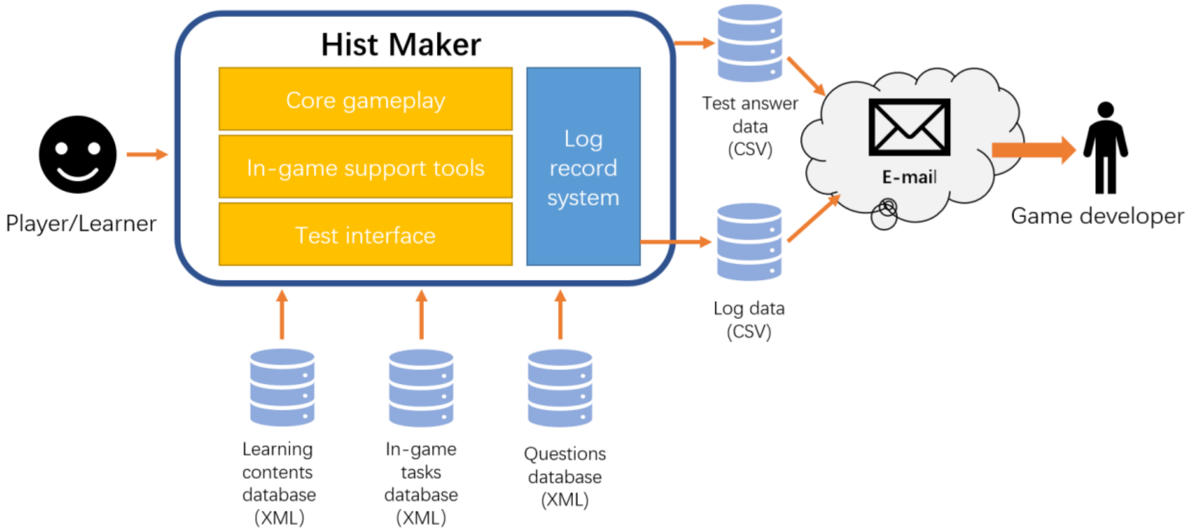

Figure 6. The database structure of the game

The test for each stage included seven multiple-choice questions. These questions are prepared based on the learning content in the game, and following discussions with a history teacher in a high school in mainland China, we modified the questions to ensure reliability and validity. Each question had three answer options and an “I don’t know” option, and there was only one correct response for each question. Therefore, the test is presented as follows: “Question: The Yanhuang Alliance fought in the land of () and defeated Chiyou, an important event leading to the unification of the Chinese tribe. Answer: A. Zhuolu; B. Banquan; C. Jizhou; D. I don’t know.” An analysis of the test results can directly show the learning effects on learners’ mastery of the content and how their level of knowledge changed while playing the game. Providing correct answers to all the questions indicated the best learning effect.

The recorded gameplay log data included not only the type and frequency of each operation but also various pieces of contextual information, such as timestamps and information about the elements and formulas that learners identified. Some examples of recorded log data are shown in Table 2. Therefore, the sequence of actions taken to identify formulas can be extracted from the log data. Further, we also collected some pieces of demographic information, such as the gender and educational background of each learner, through pre-questionnaires.

Table 2. Examples of recorded log data

Player ID	Type of operation	Contextual information 1	Contextual information 2	Contextual information 3	Contextual information 4
1001	Select an element	4/24/2019 9:00:36	Right	ELE_HUANGDI	CATE_FIGURE
1005	Attempt to combine elements	5/12/2019 15:28:47	ELE_HUANGDI	ELE_TRIBE	Fail
1020	Close the instruction text panel	3/4/2019 20:01:55	LEADER_PLUS_TRIBE_YOUXIONG	Null	Null
1035	Request a hint	6/22/2019 13:15:00	Hint tool	Hint exists	Null

5. Results

5.1. Detecting learning path patterns and examining learning effects

We implement the proposed approach by programming in R language. As a result of the utilization of the analytical approach, we obtained three clusters of learners, each believed to represent a specific learning path pattern. Specifically, 166 learners were in Cluster 1; 374 learners were in Cluster 2; and only 8 learners were in Cluster 3. Although the results were unbalanced, the clusters were determined to be far enough apart based on the merging dendrogram of the hierarchical cluster analysis. Cluster 3 was much smaller than the others; thus, it may be worthwhile discussing the learning pattern in this cluster.

In this study, the results of the pre- and post-tests demonstrate learning effects. However, each test question included the option “I don’t know,” which cannot be considered a wrong answer; thus, a simple calculation of the test scores is not suitable for measurement. To address this problem, we coded the changes in answers to the same questions on the pre- and post-tests with reference to White’s research (2012) that dealt with a similar situation. The criteria of the code are shown in Table 3, and the information about the players’ test answers and length of gameplay is shown in Table 4.

Table 3. Criteria of coding

Answer in Pre-test	Answer in Post-test	Code
Wrong answer or “I don’t know”	Correct answer	“Better”
Correct answer	Correct answer	“Equivalent”
Correct answer	Wrong answer or “I don’t know”	“Worse”
“I don’t know”	Wrong answer	“Misunderstood”
“I don’t know”	“I don’t know”	“No effect”
Wrong answer	Wrong answer or “I don’t know”	“No effect”

Table 4. Results of all players

Attribute	Mean	*SD*	Maximum	Minimum
Number of Code “Better”	2.16	1.47	7	0
Number of Code “Equivalent”	2.28	1.82	7	0
Number of Code “Worse”	0.39	0.64	4	0
Number of Code “Misunderstood”	0.62	1.13	7	0
Number of Code “No effect”	1.55	1.45	7	0
Length of gameplay (milliseconds)	1788313	5009032	93585705	451200

The number of each type of code can demonstrate the overall circumstances of learning effects for a single cluster or individual learner. For example, the number of “Better” responses can show how players acquired new knowledge with a lack of prior knowledge or how they corrected misconceptions; the number of "Equivalent" responses is also related to a relatively positive learning effect, since it shows instances in which correct knowledge of the concept was maintained.

Therefore, to examine whether learning path patterns can influence learning effects, we used one-way analysis of variance and post-hoc comparisons to identify the differences between the clusters' means for each type of code. The results of the statistical analysis are shown in Table 5. Based on these results, we observe that there are significant differences between the clusters in the codes "Equivalent," "Misunderstood," and "No effect." The three clusters did not demonstrate any significant differences in length of gameplay.

Table 5. Results of one-way analysis of variance and post-hoc comparisons

Attribute	Cluster 1 *M* (*SD*)	Cluster 2 *M* (*SD*)	Cluster 3 *M* (*SD*)	*F*	*p*	Post-hoc Comparison
Number of Code "Better"	2.25 (1.45)	2.13 (1.48)	1.50 (1.20)	1.29	.28	None
Number of Code "Equivalent"	2.54 (1.76)	2.20 (1.84)	0.63 (0.92)	5.50	.004*	C1>C3*; C2>C3*
Number of Code "Worse"	0.39 (0.61)	0.40 (0.66)	0.50 (0.76)	0.12	.88	None
Number of Code "Misunderstood"	0.40 (0.75)	0.72 (1.25)	0.75 (1.04)	4.52	.01*	C2>C1*
Number of Code "No effect"	1.41 (1.14)	1.56 (1.54)	3.63(1.41)	9.293	< .001*	C3>C1* C3>C2*
Length of gameplay (milliseconds)	1677317 (2903344)	1851062 (5748510)	1157924 (373811)	0.13	.88	None

Note. $^{*}p < .05$.

5.2. The relationship between learning path patterns and learning effects

The mean value for a code can indicate the situation of the learning effects of a cluster; for the codes that are significantly different, it is believed that the code "Equivalent" indicates relatively positive effects of keeping correct prior knowledges, while "Misunderstood" and "No effect" suggest negative effects. Accordingly, based on a comparison of the specific significant differences between clusters, we concluded that players in different clusters experienced diverse effects, which also implies correlations between learning path patterns and learning effects. Based on the results of the post-hoc comparison, it can be concluded that the learning effects of the players in Cluster 1 were more positive than those of their counterparts in Cluster 2; as for the learning effects of the players in Cluster 3, they represented a distinctive learning pattern used by the few players who fared the worst.

5.3. Explanation of learning path patterns

Besides discussing the relationships between learning path patterns and learning effects, it is important to explain the concrete patterns of learning paths. Even when traditional statistical methods can be used to confirm that different patterns of content acquisition lead to different effects, the results still do not tell us what the learning path patterns are for clusters. Without this information, modifying the design of a game to eliminate a "bad learning path" and improve the game's quality remains difficult. To elucidate the learning path patterns, especially in the clusters that included many learners, systematic methods of analysis need to be used. In this study, we utilized two methodologies: sorting out the most common sub-sequences and building a process to extract a representative sequence from each cluster.

5.3.1. Finding the most common sub-sequences

Since the learning path pattern-detection approach is based on the Levenshtein distance and hierarchy cluster analysis, it is easy to conclude that there should be short Levenshtein distances between learners in the same cluster. Applying the definition of Levenshtein distance, we inferred that characteristic-strings with short Levenshtein distances shared more common sub-sequences. The length of valuable common sub-sequences may not be great for a large cluster because the proportion of long sub-sequences is often very small, and the representation is not adequate. Therefore, the proportions and quantity are assigned more importance than the length of the sub-sequences.

The learning path characteristic-strings and the results of efforts to detect the most common sub-sequences of the eight learners in Cluster 3 are shown in Tables 6 and 7. Based on the results, we conclude that the sub-sequence "STU" made up a very large proportion and that this sub-sequence was present at the end of the learning acquisition sequence. "STU" represents formulas related to the last two sovereigns in the level "The Five Sovereigns era": Yao and Shun. Thus, the learning path for Cluster 3 included learning all the stories about successions to the throne and the contributions of other sovereigns, then gaining knowledge about Yao and Shun.

Table 6. Learning path characteristic-strings in Cluster 3

Temporary Player ID	Learning path
3-1	ACBDIJFKXENZOPHMQYVRWSTU
3-2	ABGFJCIDELKXNZHOQPYRWSMTU
3-3	BAGFJIDKXHVMLNZOQPYRSTWU
3-4	ACBIJFLKDHVNOPQXZMRYWSTU
3-5	ACBIJLKXDHENZOPQYRMSTU
3-6	ABCILDEHMJNOQYZRSTU
3-7	ABFDCGELKHMXNOQYPZRSTU
3-8	BDAFCEHLNZMOPGKQRYSTU

Table 7. Parts of common sub-sequences in Cluster 3

Sub-sequence	Frequency
ST	7
TU	7
STU	6
NZ	5
KX	4
OP	4
QY	4
LK	4
OQ	4

Table 8. Parts of the most common sub-sequences and comparison between Clusters 1 and 2

Sub-sequence	Frequency in Cluster 1	Proportion in Cluster 1	Frequency in Cluster 2	Proportion in Cluster 2	Difference Between Proportions (Cluster 1− Cluster 2)	Difference Between Proportions (Absolute Value)
NOQRS	134	80.72%	225	60.16%	20.56%	20.56%
NOQR	135	81.33%	230	61.50%	19.83%	19.83%
NOQ	146	87.95%	257	68.72%	19.24%	19.24%
MN	2	1.20%	72	19.25%	−18.05%	18.05%
LM	50	30.12%	47	12.57%	17.55%	17.55%
MNO	2	1.20%	70	18.72%	−17.51%	17.51%
MNOQ	1	0.60%	65	17.38%	−16.78%	16.78%
NO	153	92.17%	284	75.94%	16.23%	16.23%
SW	3	1.81%	67	17.91%	−16.11%	16.11%
RSK	28	16.87%	3	0.80%	16.07%	16.07%
SK	28	16.87%	3	0.80%	16.07%	16.07%
HM	4	2.41%	69	18.45%	−16.04%	16.04%
RSW	3	1.81%	66	17.65%	−15.84%	15.84%
NOQRSL	27	16.27%	2	0.53%	15.73%	15.73%
MNOQR	1	0.60%	61	16.31%	−15.71%	15.71%
OQRSL	27	16.27%	3	0.80%	15.46%	15.46%
QRSL	27	16.27%	3	0.80%	15.46%	15.46%
RSL	27	16.27%	3	0.80%	15.46%	15.46%
SL	27	16.27%	3	0.80%	15.46%	15.46%
MNOQRS	1	0.60%	59	15.78%	−15.17%	15.17%

As for the large clusters, Clusters 1 and 2, existing featured sub-sequences accounting for large proportions were unusual, so drawing a comparison between the proportions of sub-sequences enabled us to discuss the specific characteristics of the learning path patterns. Thus, we arranged the sequences in order of the differences in proportions between Clusters 1 and 2. The results of our effort to detect the most common sub-sequences and a comparison of them are shown in Table 8; the results were sorted by the absolute values of the differences. From these results, we observe that the proportions of the sequences "MNOQRS," "RSW," and some of their sub-sequences were relatively high in Cluster 2, while the proportions of these sequences in Cluster 1 were extremely low. Contrariwise, the learning path sequences in Cluster 1 included many instances of "NOQRSL," "RSK," and some of their sub-sequences, while Cluster 2 showed few examples of these patterns. Further, although "NOQRS" and some of its sub-sequences accounted for the greatest differences between the two clusters, they still accounted for a relatively large proportion of both clusters.

"NOQRS" included the formulas related to Huangdi becoming the sovereign of China and hereditary succession until the reign of Sovereign Yao. Since in all these successions, the sovereigns passed the throne to a family member of the next generation, such as a son or nephew, players easily discovered that the formula "one of the sovereigns + Son generation" would work in several instances; thus, "NOQRS" accounted for a large proportion of both clusters. The alphabetical codes "K," "L," and "M" represented the formulas related to the contributions of Huangdi, Yandi, and Chiyou, three important historical figures in the pre-unification era. Thus, it can be observed that the learners in Cluster 1 tended to learn about the secondary part of the "pre-unification era" section after learning about the primary part of the "post-unification era" section, while the order of content acquisition was reversed in Cluster 2.

6. Discussion

Using these two methods, we can conclude that the presence of the "STU" learning formula at the end of the sequence was the distinctive feature of Cluster 3's learning path pattern. The difference between Clusters 1 and 2 can be seen in the order in which the participants learned about the secondary part of the pre-unification era section and the primary part of the section about the post-unification era.

We inferred that learners in Cluster 3 experienced negative learning effects perhaps because the story of Yao and Shun is familiar to most Chinese, so the content covered in the "STU" pattern could be considered prior knowledge to some degree. Information about other sovereigns, especially those who ruled after Huangdi, is not quite as widely known, but these sovereigns had some relationship with Yao and Shun. Thus, when comparing the clusters, it appears that the learners in Cluster 3 built fewer connections between new knowledge about other sovereigns and their prior knowledge about Yao and Shun because they did not learn anything about Yao or Shun until the end of the level. Although the sample size of Cluster 3 was so small so that the persuasiveness of the inference was compromised, this inference can still provide a possible direction for modifying the game's design.

Regarding why the players in Cluster 1 experienced the most positive learning effects, based on the theory of the cognitive structures of narrative discourse (Thorndyke, 1977), we propose that the order in Cluster 1 indicates that there is a strong temporal and causal character involved in learning the primary parts of the content related to the pre-unification era and the post-unification era; thus, the learning paths in Cluster 1 are constructed relatively efficiently, which may lead to especially positive learning effects.

There was no significant difference between the clusters in terms of the length of gameplay, which means that although the amount of time spent learning can be an influential factor in constructing learning paths, it was not an important variable in this study. We found that the standard deviation of time spent playing the game was extremely large; we believe that this may be because the length of gameplay was affected by many factors besides behavioral patterns and content acquisition routes and that there may have also been some factors in the external environments of the players that were difficult to infer from the log data alone.

Discussion of the reasons that different patterns may lead to different effects can help us obtain clues to improving the quality of educational games. Since we can use the rules guiding combinations of elements to control the order in which players discover formulas and learn pieces of knowledge, we can modify the design to help players avoid taking a "bad learning path" and possibly help them choose a more effective path instead.

7. Conclusion

Our studies revolved around the development of analytical approaches by applying LA technology to build a game-embedded assessment to examine the potential value of learning paths in precision education for improving the quality of the educational game. The approach is centered on cluster analysis, which is considered a type of AI method. We applied the analytical approach to the educational game *Hist Maker*, and 548 samples were categorized into three clusters, with each representing a learning path pattern. Specifically, a minor pattern has been detected and learners with this pattern have significantly worse learning effects than others; hence, this pattern can indicate an "at risk" status for precision education. The results indicated that the proposed approach can detect non-normative (but featured) patterns, which we consider a meaningful tool for supporting the realization of precision education. After the statistical examination and discussion of the learning patterns in each cluster, we conclude that the consideration of learning paths can help us to realize precision education in a game-based learning environment. Additionally, we proposed a method to explain the specific learning path patterns in each cluster. The practice in this study proved that explanatory methods can help developers understand the analytical results and consider precision education from a game design perspective.

7.1. Contributions of this study and implications for practice

This study provides empirical evidence that the learning path with regard to learning content can influence learning in a game-based environment. For the precision education system that regards "having a bad learning effect" as "risk," the results of the analysis indicate that the learning path is a factor needing consideration. We encourage other researchers to focus on contextual data of interactions that are directly related to content, such as learning paths, in order to improve the accuracy of precision education predictions. Additionally, this study proposed a practically validated analytical approach to detect and interpret learning path patterns in *Hist Maker*. Nevertheless, while changing the granularity of the coded content, this approach also has potential for application to other learning environments based on concept maps and even all learning environments that aim for knowledge acquisition. Lastly, the proposed approach also includes a method of interpreting detected patterns. With the discussion of specific contents and cognitive psychology theories, this approach offers a comprehensive understanding and a deeper insight into learners' behavior patterns and cognitive processes. We encourage other researchers to explore approaches that consider the results of such analysis to gain a deeper understanding of learner behavior in order to provide more evidence for designing a precision education system.

7.2. Recommendations and future works

Despite the high suitability of the analytical approach in this study, as identified in practice, some work remains for the future. First, it is imperative to broaden the examination of the applicability of the proposed approach beyond the single game level examined in this study. The versatility of the analytical approach needs to be examined for other learning content, other game levels, and even other learning environments. Second, this study concluded that the learning path is an important influential factor in precision education, although variables such as the learner's personal attributes and the device platform can influence the learning effects and learning behaviors, and the optimal learning path for each learner is also governed by these variables (Su, 2017). However, they were not collected or analyzed in this study. Therefore, we recommend that future research examine the interaction between learning paths and these variables and the overall effect on learning effects in order to realize personalized interventions in precision education. Third, this study proposed an approach to analyze already collected data, but a precision education system still needs algorithms that can predict learning effects through an analysis of learning paths in the process (Hart, 2016). It will be necessary in the future to explore an approach that presents the right time to provide interventions.

Acknowledgement

This research is supported by JSPS KAKENHI Grants Nos. JP19H01716 and JP18K18657.

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