# Design and Development of Visualization Approaches for Informal Learning Game Logs

**Xuanqi Feng**
Graduate School of Human-Environment Studies, Kyushu University, Japan
744 Motooka Nishi-ku Fukuoka, Japan
dukefeng@mark-lab.net

**Masanori Yamada**
Faculty of Arts and Science, Kyushu University, Japan
744 Motooka Nishi-ku Fukuoka, Japan
mark@mark-lab.net

## ABSTRACT
Given the non-face-to-face context of educational online games, the learning process cannot be observed directly, creating a problem for the evaluation of informal learning. Methods that concentrate on employing gameplay log data such as learning analytics and game-embedded assessment are considered to be able to solve this problem. In our former study, we proposed cluster analysis; however, this approach has the inherent limitation of not being able to deal with more than a few parameters, and it limits the deeper insights we may gain into the players' learning process. In this study, our aim was to determine the interrelationship between player behavior and exploration progress in stages. For this purpose, we designed and developed two visualization approaches focused on individuals and groups, and their usability was evaluated through semi-structured interviews.

## Keywords
mobile learning, informal learning, game-based learning, learning analytics, data visualization

## INTRODUCTION

### Digital Game-Based Learning and Mobile Learning
Considering some features of digital games such as "clear goals" or "plenty of interaction" to be important components of effective learning environments, some learning science researchers (e.g., Prensky 2001; Shute 2013) have asserted that digital games can be innovative learning environments or educational tools and proposed the concept of "Digital Game-Based Learning (DGBL)."

Furthermore, with the development of mobile technology and cross-platform software technology, today it is convenient for users to run software anywhere on their smartphones, tablets, or laptops. To make use of these technologies to support education, the concept of "mobile learning" arose, a learning model that allows learners to acquire learning materials anytime and anywhere (Lan and Sie 2010). Therefore, it is meaningful to combine DGBL and mobile learning to form the concept of "mobile

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game-based learning.” Some researchers have proved the learning effectiveness of educational mobile games. For example, in Chang and Yang’s study (2016), they found that utilization of a math learning game app for 5th-grade elementary students could enhance students’ interest in learning math as well as learning effectiveness. Research by Troussas et al. (2019) showed that utilization of a mobile game-based learning application they developed could support higher education students in improving their knowledge level and that mobile game-based learning is also effective in the field of higher education.

## Educational Games of Informal Learning

Since ubiquity and spontaneity are important basic characteristics of mobile learning (Ozdamli and Cavus 2011), mobile applications can support learning in informal settings outside the classroom because of their portability. Joo and Kim’s research (2009) showed that such an educational environment, where students can learn without constraints of time or place, can enable them to make full use of the available instructions and thereby create a more effective, creative learning process. Mobile educational games are therefore appropriate for application in the field of informal learning.

According to the definition proposed by the Organization for Economic Co-operation and Development, informal learning refers to learning resulting from daily activities related to work, family life, and leisure (Werquin 2007). In contrast to formal learning in school, the structure of informal learning is not organized or guided by a rigorous curriculum. It is always considered experiential and spontaneous. Even though participation in informal learning is not compulsory, and the expected consequences are not specific (Squire and Patterson 2010), from the viewpoint of lifelong learning, most situations in which humans acquire knowledge and skills are informal (Bank et al. 2007). Therefore, making use of the characteristics of mobile game-based learning to support informal learning is meaningful for education.

## A Problem in Informal Learning Assessment

Nevertheless, a problem exists with the development and evaluation of games for informal learning, as it often occurs in non-face-to-face situations, and there is a lack of teacher observation of the learning process. This “observation problem” is especially prominent in mobile learning games, which can be played anywhere. As a result, related research mainly employs external assessment such as tests and questionnaires (Fujimoto and Yamada 2013), making learning activities into a “black box.” In such cases, information about the learning process is insufficient, and, consequently, it is difficult to explain the practical results of the utilization of informal learning games or to build a formative assessment that can examine the effectiveness of a learning game and then provide feedback on how to improve it (Loh 2011).

To face such a problem, we developed a function that can trace the players’ gameplay log. And to deal with the collected data, we proposed a data analysis approach of using cluster analysis, but this approach has the inherent limitation of not being able to deal with more than a few parameters, and it limits the deeper insights we may gain into the players’ learning process. In this study, we will use visualization approaches in the hope of making up for defects. A further introduction about our prior work will be in the next section.

## PRIOR WORK

### Literature Review

#### *Game-embedded assessment and learning analytics*

Methods that employ gameplay log data are supposed to be effective in solving the "observation problem" of informal learning in game-based learning. A new approach called "game-embedded assessment" has been proposed for the assessment of educational games (Shute et al. 2009). Instead of using tests or questionnaires outside the game, game-embedded assessment focuses on the learning/playing process and aims to assess learner activities by analyzing collected learner operation logs. A number of studies have shown that game-embedded assessment provides an effective way to assess player behavior, and it covers a wide range from problem-solving performance (Shute el al. 2016) to self -regulated learning skills (Sabourin 2013). On the other hand, Learning Analytics (LA) is a new area that focuses on analyzing the interaction between learners and the educational environment (Elias 2011). In the field of LA, researchers are studying how learners perform actions in a learning environment and are attempting to use data analysis to help make decisions about modifications to the educational system. LA has been widely utilized, not only in educational games but also in online learning systems such as online courses (Hu et al. 2019).

#### *Visualization approaches in LA*

There are various analytical approaches in the field of LA, e.g., cluster analysis, process mining, and data visualization. A visualization approach is often used to display the traced learning process in an intuitive way to help researchers understand learner behavior and derive deeper insights about learning. Visualization is especially suited to be applied to learning that occurs in informal situations (Shimata 2015). Additionally, visualization not only assists developers of learning environments by providing suggestions for improvement like other LA approaches; it also supports teachers and learners by enabling them to monitor the learners' learning process and situations (Shimata 2015). Providing visualized learning logs, in particular, to learners can support their self-regulated learning (Yen 2018) and promote participation in learning (Jin 2017).

#### *Visualization approaches for games*

Visualization is also an important analytical approach in the game development industry. To extract valuable information from detailed gameplay logs, graphical representations from visualization of the data play an important role, as they enable game developers to explore and derive insights from the data in an efficient and effective way (Wallner and Kriglstein 2015). Visualization of gameplay data is used widely in entertainment digital games to help developers modify their game designs (Wallner et al. 2013). With respect to the educational purposes, visualization can help detect the types of gameplay behavior that lead to better learning effects (Scarlatos and Scarlatos 2010) or determine the different behaviors of high-performance and low-performance learners (Liu et al. 2016).

### ***Hist Maker* Educational Game**

#### *Overall introduction*

*Hist Maker* (2018) is the title of an educational game for informal learning developed by the authors. *Hist Maker* is a puzzle game designed to enable players to learn about historical concepts through the playing process. The game runs on Android or Windows OS platforms, so users can play anywhere on their smartphones or PCs, and it has been published on game application platforms such as Steam. Players can access the game spontaneously in informal settings, meaning that learning with *Hist Maker* is considered a kind of informal learning. In this game, there are several stages, and each stage contains historical knowledge about one era in one country. Two assessment systems are embedded in the game: a test system for external assessment and a game telemetry (gameplay log tracing system) for game-embedded assessment.

### *Core gameplay*

The core gameplay is based on the theory of meaningful learning and concept maps. These theories emphasize the importance of concentrating on relationships between new knowledge and existing knowledge, which would make the learning process more effective than rote learning (Novak et al. 2008). The core gameplay involves the mechanism of "element and formula." In the game, an "element" represents a knowledge concept about history, and the relationships among elements are presented by "formulas" in the form of "element A + element B = element C," meaning that element C can be acquired from the combination (interaction) of elements A and B. The "formulas" can be referred to as an alternative way to display concept maps, as the transformation in Figures 1 and 2 shows. However, concept maps are not presented in the game because, according to Charsky's research (2011), showing complex concept maps directly to students could decrease their learning motivation in a game-based learning environment. At the beginning of a game stage, players only have a few elements and acquire new ones by determining the correct combination of formulas. When players determine a new formula, they receive instruction explaining the relationship between the knowledge concepts in the new elements and the existing knowledge in acquired elements. Thus, the gameplay procedure is considered to support meaningful learning. Moreover, the mechanism of "element and formula" is expected to be able to be applied to other subjects not limited to history. Thus, the game "Hist Maker" is considered to be potential to provide a domain-general learning game framework and the log data analysis approach about this game may have general applicability.

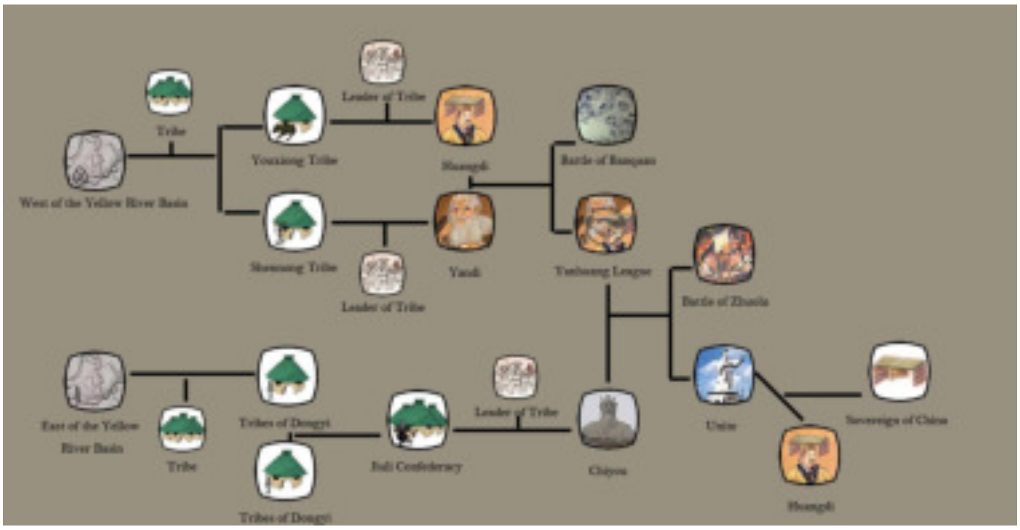


**Figure 1:** Part of the concept map showing knowledge concepts in the "Five Emperors Era" stage

### *Supporting tools*

To make the educational game more effective, we developed several in-game tools based on some theories of digital game-based learning to support players' learning and playing. There are three main types of tools in *Hist Maker*: Task List, Hint System, and database tools.

**Figure 2:** Parts of formulas transformed from the concept map shown in Figure 1

Based on the assertion that clarified goals in the game can inform players of what to do and improve their learning motivation (Malone and Lepper 1987; Shute 2013), we developed the Task List tool to provide a series of tasks (missions) in the game. Moreover, it should be emphasized that each stage has a “Clear Task,” and completion of this task means “Stage Cleared”; i.e., most of the stage’s content has been explored. After “Stage Cleared,” the post-test of this stage is unlocked, and players can choose to finish the stage or continue to explore the whole stage with more difficult challenges.

Furthermore, according to the theory that the learning environment and difficulty of challenges in the game should be adapted to player capability (Gee 2003), we developed the Hint System tool; when the game difficulty level is too high for players who lack prior knowledge, they can lower the difficulty level by asking for hints to solve the puzzle.

Additionally, since Bera et al. (2006) mentioned that database tools recording information about items in the game can become cognitive tools sharing the cognitive load, we developed database tools such as “Showing Acquired Elements” and “Showing Acquired Formulas.”


**Figure 3:** User interfaces in *Hist Maker*

## Purpose of the Study

### *Former study: cluster analysis approach*

From the literature review, we know that the use of game-embedded assessment based on the LA viewpoint may solve the "observation problem" of informal learning in educational games. Therefore, in our former study (Feng and Yamada, 2019), we released the *Hist Maker* game and collected the gameplay log data and results of tests from 185 players in mainland China. Then, we proposed a data analysis approach integrating a traditional statistical model (e.g., analysis of variance) and cluster analysis and used it to deal with the collected data. We obtained three groups from the results of the cluster analysis. Each group represents a type of behavior pattern, and different groups have different learning effects. These three groups were named "Explore Group," "Hint Group," and "Negative Group," and their situations are shown in Table 1.

| Group | Completed task number | Completeness of the stage | Frequency of asking for hint | Frequency of using other tools | Learning results |
|---|---|---|---|---|---|
| Explore Group | high | high | relatively low | high | relatively positive |
| Hint Group | middle | middle | high | high | positive |
| Negative Group | low | low | relatively low | low | negative |

**Table 1:** The situations of the three groups

### *A new approach: visualization*

In the discussion of the limitations of our analytical approach, we included the inherent limitations of cluster analysis, which can only deal with a few parameters. In this approach, player behavior is only expressed through the frequency of various actions, which provides limited insights into their learning process. Because of this inherent limitation, some of our demands could not be met.

While exploring a stage, a player obtains more "elements" by determining the correct combinations of "formulas"; the more elements the player acquires, the more difficult it is to find the right combination. Thus, we consider that as exploration in the stage progresses, the difficulty of gameplay increases, and we think it is meaningful to investigate how player behavior changes with progression of in-game exploration. Our aim is therefore to determine the relationship between the players' behavior and their progression in the game. However, it is not possible to fulfil our objective using only a cluster analysis approach.

From the game telemetry, we collected gameplay log data with many details such as timestamps of each action and the actions' time sequences. Since the inherent limitation of cluster analysis can only be solved by using another analytical approach, it is necessary and possible to develop a new approach to help us understand player behavior.

Based on the literature reviews, a visualization approach is considered suited to meeting our objective and compensating for the limitation of the cluster analysis approach. The following research question is proposed: Can a visualization approach support the analysis of the relationship between player behavior and exploration progress in the stage? In the general direction of utilizing game-embedded assessment and learning analytics to solve the "observation problem" of informal learning in educational games, the objective of this study was to develop a visualization approach for gameplay log data analysis.

## VISUALIZATION APPROACH 1: FOCUSING ON GROUPS

### Selection of Representation

Since we had divided the players whose gameplay data were collected into three groups based on cluster analysis, we considered it meaningful to know the overall situation of player behavior in each group and compare them. Therefore, we decide to develop a visualization approach with the aim of determining the overall group image of player behavior changes based on exploration progress in the stage. As for the selection of representation, in Wallner and Kriglstein's literature review (2013) about visualization-based analysis of gameplay data, they classified visualization representations into five categories. There are "charts and diagrams" and "heat maps" in these five categories.

Charts and diagrams can display the interrelationship between various data and are useful for answering specific questions about data analysis. Hence, although it is difficult for them to display gameplay in detail and support exploratory data analysis, they are still used in a large number of gameplay data analysis tools (e.g., Scarlatos and Scarlatos 2010). Given that we had a specific aim, charts and diagrams were regarded as appropriate representation tools.

Heat maps are usually utilized to show spatial data about players' location information— different colors on the map represent the frequency of players appearing there. It seems that heat maps are more suited for virtual world games, but we assumed that heat maps could also help us observe the frequency of players using various tools in different progress phases, which might meet our objective. Thus, "heat maps" were selected as one of the representation tools for the visualization focusing on player group gameplay.

### Design

Every stage has several "formulas," and the players explore the stage by determining new "formulas" in combinations of "elements." Thus, the number of formulas players acquire is considered to be a good metric to represent exploration progress in the stage. We defined a progress phase as the period from the acquisition of the last "formula" (or the beginning of the game) to the acquisition of another new formula. Action frequency still represents player behavior as it does in the cluster analysis approach. However, in contrast to the cluster analysis approach, visualization can show the frequency in each progress phase, and, to show the overall situation of a group, the average frequency of each group of players is calculated.

For the representation of charts, we chose line charts. Numbers on the x-axis represent the number of new formulas acquired by a player and expresses the progress phase. For example, the value of 3 of x refers to the period from the time the player obtains a new formula for the third time to the time he/she determines another new formula. For the same rule, the value of 0 of x refers to the period from the beginning of the game to the time the player determines a new formula. Numbers on the y-axis represent the average frequency of a specific action for players in a group. To facilitate the comparison of groups, line graphs for each group are drawn in one chart.

The heat map representation displays a matrix of rectangles. The matrix columns represent the progress phase with the same definition as that of the line chart. The matrix rows represent the player groups, and because the players have been divided into three groups through cluster analysis, the heat maps have three rows. This facilitates the comparison of groups by enabling reading of the heat map in a vertical direction. The color of each rectangle expresses the average frequency of one action in one progress phase of the players in one group. The higher the frequency, the lighter the rectangle's color. Moreover, a line chart and heat map are drawn in one picture. Whether it is a line chart or a heat map, a picture can only display the frequency of one action; hence, a number of pictures for various actions should be drawn.

## Results

Based on the design introduced above, we developed a visualization tool to automatically read the gameplay log and draw the line chart and heat map. The results are shown in Figure 5. The actions we chose to observe include the utilization of some of the in-game supporting tools. These actions are considered valuable to observe because their frequency was verified to show significant difference ($p<0.05$) among groups through analysis of variance in our former study. Moreover, we were interested in how many times the players tried to combine elements and failed in a progress phase; therefore, we also chose the action "Click the 'combine' button" to observe, even though its frequency showed no significant difference ($p<0.05$) among groups.

What's more, we noticed that not all the players determined all of the formulas to completely explore the stage, since continuing exploration after "stage cleared" is considered to be a difficult challenge that is not compulsory. This means that in a later progress phase, some players may have finished the stage, and action frequency is certainly 0. Our visualization tool also drew a line chart and heat map to display the interrelationship between the progress phase and the number of players in the group who had not finished the stage in the current progress phase (Figure 4). However, this fact creates a dilemma around the method of calculating average frequency for a later progress phase, with two solutions being possible. Solution 1 (S1): The frequency of players who finished the stage should be regarded as 0, and the denominator in the average value calculation is the total number of players in the group at all times. Solution 2 (S2): These exited players should be removed, and the denominator is the number of players who remain playing in the stage.

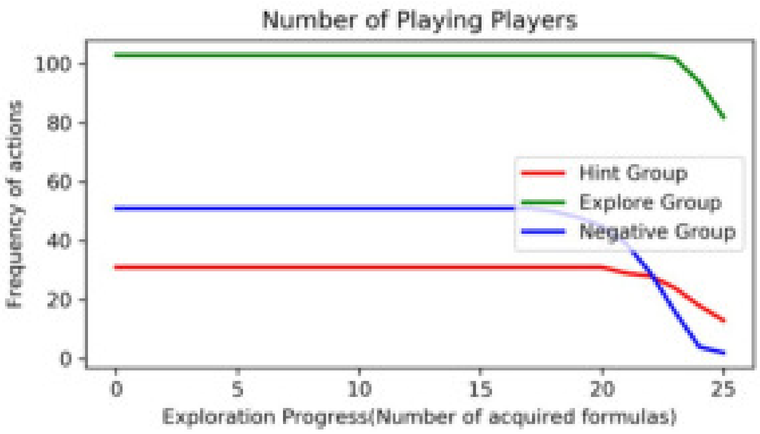


**Figure 4:** Line chart showing number of playing players in different exploration progress phases

We decided to keep both of the above solutions, since we hold that the former can show the overall attitude of a group, while the later can show players' behavioral characteristics. For example, Figure 5-1 shows the "Negative Group" players' overall negative attitude to participating in the exploration to be the same as the "Hint Group" players. However, Figure 5-2 shows that "Negative Group" players who remain playing in the stage have a much higher frequency of trial and error to determine new formulas than “Hint Group” players. A possible reason is that the remaining players in the “Negative Group” have a lower frequency of requesting a hint with the instructions for a formula (Fig 5-10), resulting in repeated attempts to combine the elements. It seems that the behavior patterns of these remaining players in the “Negative Group” are more like those of the “Explore Group” players.

Furthermore, these pictures can also help us understand the role of supporting tools in different progress phases. For example, from Figure 5-11 through Figure 5-14, it is clear that the frequency of using “Showing Acquired Elements” and “Showing Acquired Formulas” increased rapidly in later progress phases. This can be explained by the idea that when challenges in a stage become difficult, the need to utilize database tools to share the cognitive load increases; therefore, improving the design of database tools may result in better learning effects. Such insights cannot be derived from the cluster analysis approach.

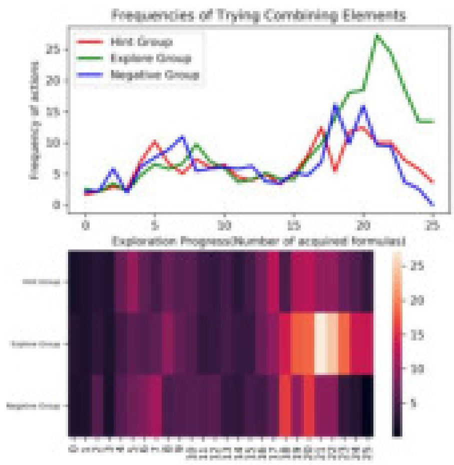


**Figure 5-1** Trying Combination (S1)

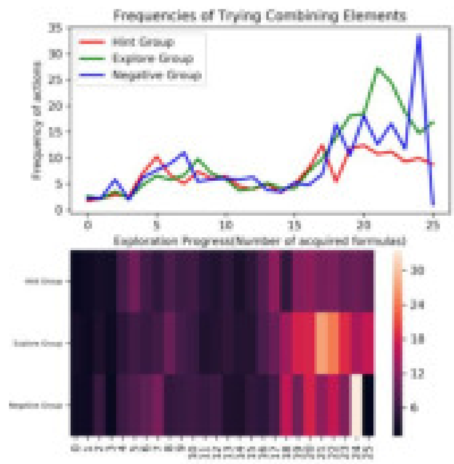


**Figure 5-2** Trying Combination (S2)

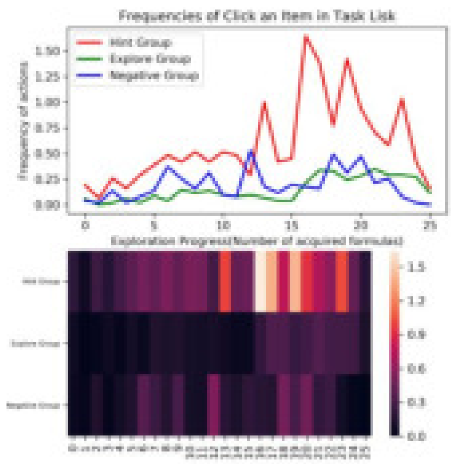


**Figure 5-3** Click Task Item (S1)

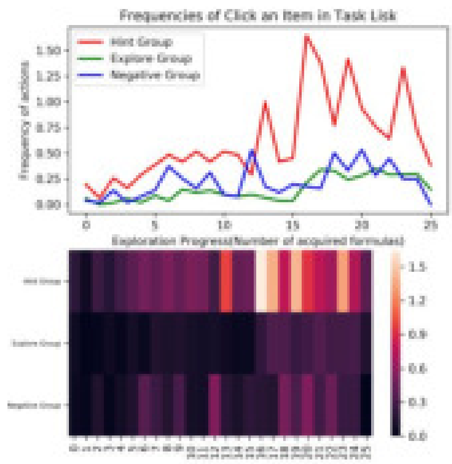


**Figure 5-4** Click Task Item (S2)

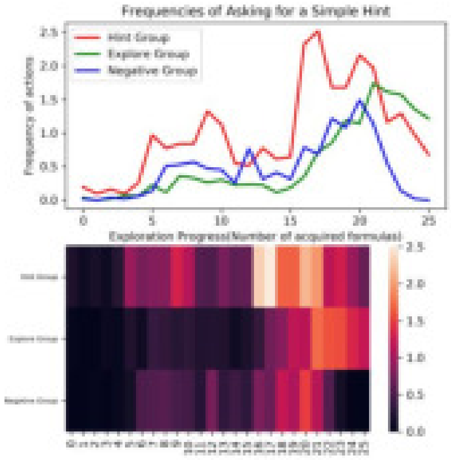


**Figure 5-5** Ask for Simple Hint (S1)

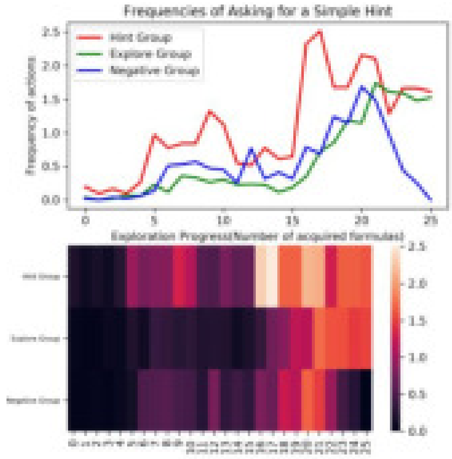


**Figure 5-6** Ask for Simple Hint (S2)

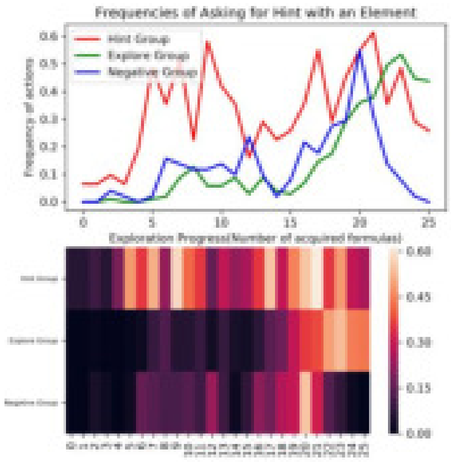


**Figure 5-7** Ask for “Element” Hint (S1)

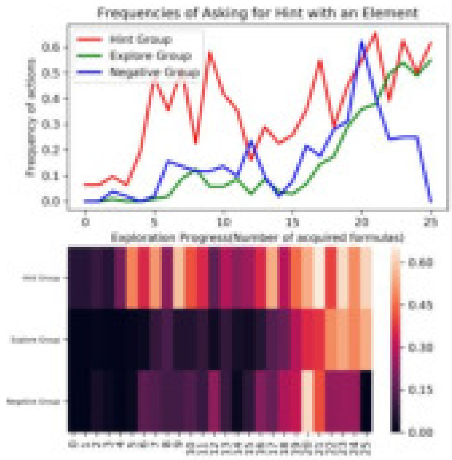


**Figure 5-8** Ask for “Element” Hint (S2)

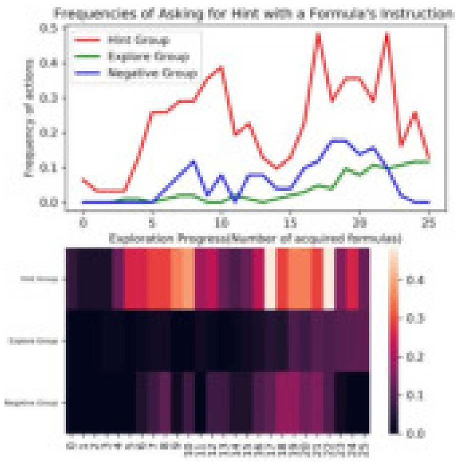


**Figure 5-9** Ask for “Instruction” Hint (S1)

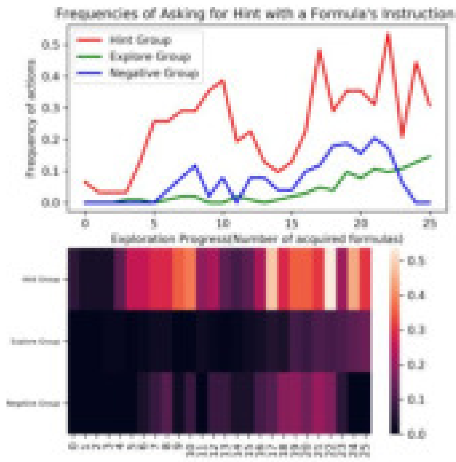


**Figure 5-10** Ask for “Instruction” Hint (S2)

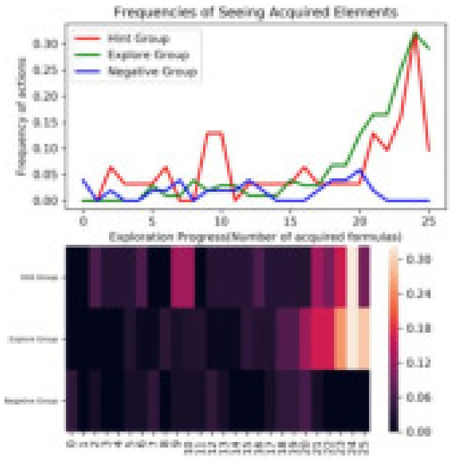


**Figure 5-11** See Acquired Elements (S1)

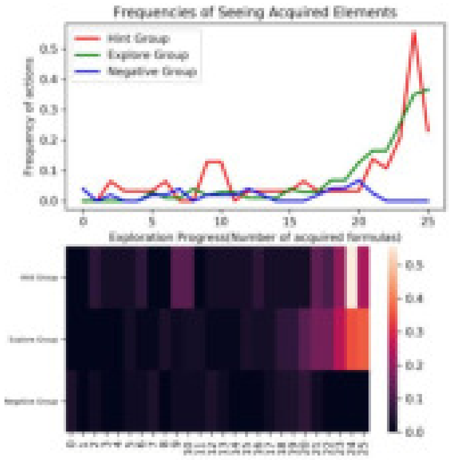


**Figure 5-12** See Acquired Elements (S2)

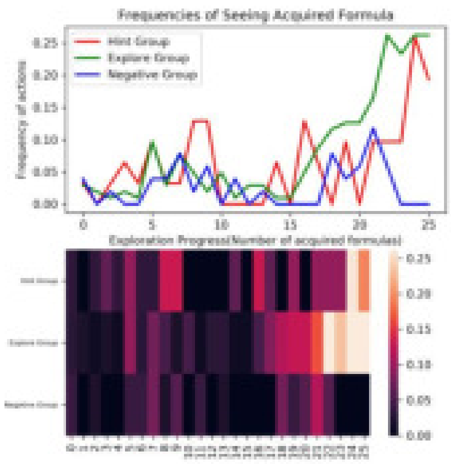


**Figure 5-13** See Acquired Formulas (S1)

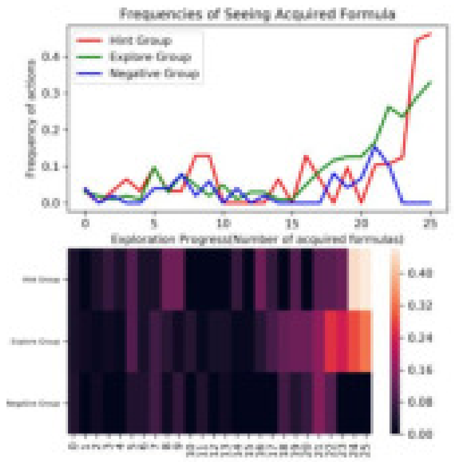


**Figure 5-14** See Acquired Formulas (S2)

**Figure 5:** Results of the visualization approach focusing on groups

## VISUALIZATION APPROACH 2: FOCUSING ON INDIVIDUALS

### Selection of Representation

The above visualization approach can indeed help us to see how player behavior changes with their exploration progress. However, using only the action frequency in different progress phases still constrains the expression of player behavior. We have collected a range of useful details about player behavior such as the time sequence of actions; therefore, another one of our objectives is to develop a visualization approach that focuses on individuals and can present the detailed actions of each player. Still, our overall objective to determine the interrelationship between gameplay behavior and exploration progress remains important.

As for representation, we believed that "node-link representation" is appropriate. "Node-link representation" is also one of the five categories of visualization representation raised by Wallner and Kriglstein (2013), and it is suited to displaying gameplay behaviors in games that are unrelated to a spatial environment such as puzzle games. Since *Hist Maker* is a puzzle game, and its gameplay has no connection to any spatial information, "node-link representation" is considered to be able to meet our objective.

More specifically, the type of "node-link representation" we use is named the "Wisteria Graph." Put forward by Kaneko et al (2015), and Kaneko et al (2018), Wisteria Graph features nodes usually representing a user's action/operation, and nodes extend vertically or horizontally by following some rules. The form of the node representing an action allows the presentation to show all actions during play for each individual player. Additionally, the extension of the nodes can be designed to be affected by the smoothness of game progress. Under such condition, Kaneko asserts that Wisteria Graph can show if a user is facing a difficult situation. Following this thinking, if we make rules that nodes' extension directions relate to exploration progress, Wisteria Graph can also express the interrelationship between gameplay behavior and exploration progress.

## Design

In our design, the modified Wisteria Graph is composed of multiple nodes and links connecting those nodes. In the graph, nodes represent the learners' actions, while links represent the action's flow. All rows and columns represent time series.

Normally, the graph extends downward with a new node below the last one. However, when the learner has determined a new formula and solved a puzzle in the game, whose concept map was simultaneously explored, the diagram will extend rightward with a new node set in a new column, i.e., extend horizontally. Hence, the rows illustrate the exploration progress of gameplay in a stage. In this way, the interrelationship between gameplay behavior and exploration progress is presented intuitively.

Different-colored nodes represent the learner's action in different categories; the corresponding relationship between the category of actions and color is shown in Table 2. The length of the link connecting the nodes in the vertical direction represents the time difference between actions; thus, timestamp information can be utilized. If there are multiple actions when using a tool such as after requesting a hint and before closing the interface panel of the "Hint System," and the player has performed several actions, the link on the left side of the circle represents the time span of use of the tool. To have an intuitive understanding, Figure 7 can be referred to as an example of Wisteria Graph.

| Color | Action Category |
|---|---|
| Red | Start the stage |
| Yellow | Click the task item |
| Yellow-green | Scroll the task list |
| White | Other actions in the "task list" |
| Light green | Request a hint |
| Green | Request a hint with an element |
| Dark green | Request a hint with an instruction |

| | |
|---|---|
| Purple | Show acquired elements |
| Violet | Show acquired formulas |
| Dark blue | Other actions in the "showing" function |
| Sky blue | Try combining the elements |
| Grey | Close the dialog box or function interface |
| Blue | Other unimportant actions |

**Table 2:** Corresponding relationships between the category of actions and color

### Result

Figure 6 shows one of the results of the developed visualization tool's implementation. However, since each player generates a huge number of actions, the drawn Wisteria Graph is so large it can't be read clearly when the complete graph is shown. Therefore, to present details in the graph, we also show part of it in Figure 7.

**Figure 6:** A complete Wisteria Graph for a player in the "Hint Group"

Looking at the Wisteria Graphs, we can observe many details concerning players' gameplay behavior such as when they concentrate on trying to combine elements continually and when they stop to request a hint or use other tools. Simultaneously, these graphs show different behaviors with all types of actions in different exploration progress phases, while a line chart or heat map can only show the situation of one type of action. In addition, from the visualization of detailed gameplay behavior, we can infer the context of players' gameplay such as the reason for their actions. For example, a series of trials of combining elements after a check of the description of a task in the task list may indicate that these trials are to acquire the new element shown in the hint. Further, a request for a hint after a series of attempts to combine elements suggests that the player maybe tried to combine elements without clues and encountered difficulty, then chose to request a hint for support. In this way, the "observation problem" in the non-face-to-face informal situation can be solved to some degree.

**Figure 7:** Part of the Wisteria Graph shown in Figure 6

## EVALUATION

To evaluate the two visualization tools we developed, we conducted semi-structured interviews with 5 researchers who major in educational technology and are focusing on research about the design and development of learning environments with the experience of more than one year. Each interview took about 1 hour including the introduction of the visualization tools. According to the literature review (Hintz, 2014), we considered that 5 experts are enough of the evaluation. The profile of these interviewees is shown in Table 3. Interviews were conducted according to the following guideline:

Part 1: Introduction of the gameplay and guide on how to read the pictures generated by the two visualization tools.

Part 2: Investigation of their research activities as well as demographics information.

Part 3: Questions about the evaluation of the visualization approach. The following questions are included: our objective is to figure out the interrelationship between player behavior and exploration progress in the stage, do you think result pictures generated by visualization tools meet our objective? Do you think the results can help the developer of "Hist Maker" understand players' gameplay and build a formative assessment? What points need improvement in these two visualization tools? Do you have other comments?

| Interviewee (Code name) | Research subject | Points of concern about visualization of users' behavior | Form of interview |
|---|---|---|---|
| Ms. C | STEAM Education & LA | Performance of each student | Face-to-face |
| Mr. G | AR enhanced language learning | Context and situation about behavior | Face-to-face |
| Ms. H | Math Education & LA | How to get insight of the behavior | Face-to-face |
| Mr. X | CSCL & LA | Presentation of the picture | Face-to-face |
| Mr. S | Science Education & LA | Inference and sense-making | Online |

**Table 3:** The situations of the three groups

We record the answers in the interviews and summarized them into the following statements. Consequently, all of the interviewees claimed that both visualization tools helped them to see the interrelationship between player behavior and exploration progress and that the generated pictures provided them with insights into understanding player behavior. This means that the two developed visualization tools could meet our objectives. In terms of representation, some comments on improvement were made. For instance, in addition to comparing groups, observing gameplay situations in a specific group is also valuable, and since gameplay behavior includes various types of actions, Ms. H and Mr. S suggested that it is better to see the line charts showing the frequency of different actions in one picture. Mr. X claimed that, blue nodes in the Wisteria Graph which stand for unimportant actions may hinder concentration on other important actions. Mr. G concerned that Wisteria Graph need to show the context information such as formulas obtained by the player in former exploration progress phases be displayed in the graph, to help modify the design of formulas in the stage.

Additionally, problems pointed out by interviewees revolved around limitations of the "Individual Approach." Although Wisteria Graphs can provide many details about how players play a game, one Wisteria Graph can only represent the behavior of one player, and conclusions drawn from reading the graph lack representativeness and, consequently, are difficult to use as evidence for improving game design. Especially, Ms. C pointed out that there is a gap between the "Group Approach" and the "Individual

Approach," and a visualization approach to show the behavior situation of players in a single group is needed.

## DISCUSSION AND CONCLUSIONS

Based on the discussion of the limitation of the cluster analysis approach for gameplay log data analysis we proposed in the former study, in this study, we proposed new visualization approaches to make full use of collected data with much detail. The objective of visualization is to present the interrelationship between player behavior and exploration progress in the stage. We developed two visualization tools, one focusing on overall behavior in a group and the other focusing on an individual's gameplay.

Based on the results of the two visualization approaches, we developed and received feedback about evaluation and determined that the developed visualization tools do meet our objectives, to some extent. The line charts, heat maps, and Wisteria Graphs generated by the visualization tools can help us to understand the interrelationship between player behavior and exploration progress in the stage and support us in improving *Hist Maker*. Furthermore, both visualization approaches have advantages and disadvantages.

The approach focusing on overall behavior in a group can smoothly utilize the grouping results from the cluster analysis approach proposed in our former study and maintains consistency between this study and the former study. Since players in different groups have different learning effects, showing the overall situation can indicate how behaviors in different exploration progress phases connect with learning effects, which can provide important clues for improving the educational game. For example, as we mentioned above, frequency of using database tools increased rapidly when the difficulty of the game increases. Based on such a result, we can develop a new function to enhance database tools on supporting cognitive process and it is expected to improve the learning effects of the game. However, in this approach, behaviors are only represented by action frequency in different exploration progress phases; their manifestation is still constrained. Even if from the generated pictures we can infer that there is some interaction among the different actions (e.g., requesting a hint may decrease the number of attempts to combine elements), we can't examine them, since the sequence of actions does not appear in the visualization results.

By contrast, a visualization approach focusing on an individual's gameplay can present the players' gameplay behaviors in more detail, including the sequence of actions and time difference between actions, which can give us insights into players' behaviors that can't be drawn from a visualization approach focusing on the group. Nevertheless, the most prominent limitation of this visualization approach is that the result of an individual can only represent an individual player; therefore, the conclusions may not apply to other players. In particular, if conclusions about the interrelationship between player behavior and learning effects lack generalizability, it is difficult to build a formative assessment based on these conclusions. Further, the results from the cluster analysis approach proposed in our former study are difficult to utilize in this approach because it is hard to prove that the observed individual is representative enough to show the overall situation of a group. Additionally, another disadvantage of this approach is that the generated Wisteria Graphs are typically very large and complex, and it would take a long time to read such graphs. This is a limitation of "node-link representation" (Andersen 2010).

From our comparison of the two visualization approaches, we can conclude that it is difficult for a visualization approach to maintain both representativeness and rich detail at the same time. Therefore, the integration of these two approaches is necessary. Observing the overall situation of a group of players' behaviors from line charts and heat maps and then utilizing Wisteria Graphs to seek deeper insights based on this macroscopic conclusion may be an effective way to apply these two approaches. Moreover, the design of visualization tools can be improved by developing new functions. For example, the Wisteria Graph approach could add a new function to show a group of players' behaviors in one exploration progress phase (a player's behavior is shown in a column, and different columns show different players' behaviors), and this new function can improve the representativeness of the approach.

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