Chapter 7
Integrating a Learning Analytics Dashboard in an Online Educational Game

J. X. Seaton, Maiga Chang and Sabine Graf

Abstract The goal of educational games is to allow players to learn unconsciously while playing. The more a player plays an educational game, the more their learning and their skills can increase. Just like in other games, players in educational games may encounter situations where they feel like they cannot make further progress like passing a level or completing a quest. If players are stuck in an educational game, then they may choose to quit playing the game, which also means that they quit learning. Especially if players quit early, the effect of the educational game will be limited and not last for too long. Therefore, providing players with information on how to improve their performance, such as when and how to play the game, which parts or skill improvement is needed to overcome a challenge and go further in the game, can help to encourage them to play the game more often and continuously. This chapter discusses how the research team integrated a learning analytics dashboard into an educational game so that the players can see their game play performance and habits, and find clues and strategies to improve their in-game performance. The proposed dashboard provides players with a variety of information that will allow them to see how their performance and skills change over time, what their weakness and strengths are and much more. This chapter talks about the design of learning analytics dashboards for educational games and explains the use of the proposed dashboard to help players improve their in-game performance through use cases with 3-month simulated gameplay data.

1 Introduction

Educational games have the potential to make learning more engaging because, unlike traditional media, games are interactive. Educational games do not just present players with information, but problems for them to solve [1]. Part of what makes a

J. X. Seaton · M. Chang (✉) · S. Graf
Athabasca University, Athabasca, Canada
e-mail: maigac@athabascau.ca

S. Graf
e-mail: sabineg@athabascau.ca

A. Tlili and M. Chang (eds.), *Data Analytics Approaches in Educational Games and Gamification Systems*, Smart Computing and Intelligence,
https://doi.org/10.1007/978-981-32-9335-9_7

game fun is that the in-game problems are challenging [1]. By framing a learning objective around such a challenge, it can be integrated into a game in a fun way. In this way, an educational game allows the player to learn by playing. Learning is implicit from the feedback they receive about the actions they have taken or choices they have made in the game [2].

However, the mere incorporation of an educational game into a learning environment is not guaranteed to increase student motivation to learn [3]. The initial novelty of an educational game can increase motivation, but that interest will fade over time as the game becomes familiar to the students [4]. Therefore, it is important for educational games to include motivational techniques that encourage continuous play [3]. An effective motivational technique in education is to highlight a learner's accomplishments [5], thus learning analytics dashboards which visualize a player's improvement could be motivational.

It is difficult for players in any game, including educational games, to connect the feedback they see in a game to how they can further improve their in-game performance. When they are leveling up, usually they are seeing more challenging and difficult quests or problems. It is common to see that they are learning through the loop of failing and re-attempting. Feedback about a failed attempt can help them play the game better [6]. Incorporating learning analytics into educational games can demonstrate to players how their gameplay is connected to their improvement in the game, provide them with an opportunity to analyze their gameplay and the effects of their playing habits on their in-game performance, and find strategies to improve their gameplay. In turn, by improving their gameplay, players automatically and implicitly improve their learning in the educational game.

The aim of this chapter is to demonstrate how learning analytics can be incorporated into an educational game. The educational game featured in this chapter focuses on improving players' metacognitive skills by playing short subgames against other players. The learning analytics dashboard presented in the chapter uses two types of charts: line graphs and scatter plots. Line graphs are used to show a player how their metacognitive skills have improved over time, and while they have played. The scatter plot visualizes how the player's performance in subgames is affected by the time of day or how long a player plays in a single sitting. The dashboard has been evaluated in a proof of concept evaluation with three months of simulated gameplay data, which demonstrates the benefits of the information presented in the dashboard.

This chapter first reviews related works on how learning analytics have been incorporated into educational games. Then it presents a general overview of the educational game where the learning analytics dashboard was implemented, followed by a description of the dashboard. Next, a proof of concept evaluation of the proposed dashboard is presented. Finally, the conclusion section summarizes the findings and discusses future work.

477240_1_En_7_Chapter ✓ TYPESET ☐ DISK ☐ LE ✓ CP Disp.:5/8/2019 Pages: 13 Layout: T1-Standard

2 Related Works

Applying learning analytics to educational games is an emerging field. Much of the motivation to incorporate learning analytics into educational games has been to understand how to use educational games for assessment [7]. Games can appear as black boxes that do not give instructors much information about the player's learning process [8]. Thus, although teachers are open to including educational games in the classroom, they are hesitant to use games to assess learning [9]. Learning analytics is seen as a way to open the black box by providing aggregate data about where players are struggling [8], and the common mistakes made by learners [7].

Educational games track and log a variety of information about players that can be used for learning analytics to work [10]. For example, an event log with a timestamp, information about when players login or reach a goal can determine how long players are playing or how long it took them to reach their goals. Additional gameplay data specific to the educational game include the player's scores, position, or decisions made in the game can all provide meaningful information about how the player progressed through the game [11].

However, while games could technically log a lot of data, it can be challenging to add learning analytics into them because typical game design often discards any variables not necessary for gameplay to optimize the performance of the game [12]. Therefore, integrating learning analytics into an existing game often means that the data collected is limited and may not provide the desired information.

Loh et al. [13] encountered this issue when incorporating learning analytics into an existing commercial game *Neverwinter Nights*. *Neverwinter Nights* was modified to be an educational game, where the path a student took through the game could tell the instructor something about the process the student used to complete his or her works. The modified educational game intercepted and logged gameplay data to create learning analytics reports for instructors. The reports contained both individual and aggregate information about the students' paths to help the instructor assess individual student's learning progress and identify common issues that students faced. One issue with integrating learning analytics into *Neverwinter Nights* was that some of the gameplay data was not descriptive enough. For example, the fact a player got a new item could be seen from the log, but how the player got the item is not known because it was not relevant to gameplay.

Educational games that are designed for the inclusion of learning analytics from the ground up can create variables and data specifically suited for learning analytics. Activities directly related to learning objectives can then be logged for later analysis. For example, the game CMX is an educational Massively Multiplayer Online Role Playing Game (MMORPG) that teaches computer programming [9]. With respect to learning analytics, the game creates reports for instructors about how players are progressing within the game. Instructors can see how many learning activities students have completed, how many errors they made, how many times a player has logged in, how long a player has played, and how many times a player has interacted with another player. To aid in assessment, instructors can also create a report that

477240_1_En_7_Chapter ☑ TYPESET ☐ DISK ☐ LE ☑ CP Disp.:5/8/2019 Pages: 13 Layout: T1-Standard

assigns students a percent score by comparing the students' data to a sample of ideal game behavior.

While many educational games use learning analytics to provide teachers with additional information, some games provide such additional information to learners. For example, the educational game eAdventure [14], which is an educational game plugin designed for edX courses, provides students with reports that assess their learning. Due to the very high number of students in edX's massively open online courses, it is very difficult to provide students with individual assessments from teachers. Therefore, eAdventure uses the existing learning analytics tools offered in edX courses to provide learners with some additional information on how they are doing in the game, including how much time they are spending playing the game; the time it took them to finished the game (or a subsection of the game), and their score in the game.

The application program interface xAPI can also aid in designing educational games that support learning analytics for assessment [8]. By using xAPI, game designers can determine what data is relevant to learning, log the data during gameplay, formatted according to xAPI specifications, and then generate different learning analytic reports. The reports can feature a variety of information and can be configured to display reports relevant to students, teachers, or administrators. For example, the game Countrix, which is an educational game about geography, utilizes xAPI to log information about student errors to create a report for the players in real-time about their error rate [11].

The learning analytics dashboard presented in this chapter differs from those discussed in that the focus is not on assessing a player's learning progress. The purpose of the dashboard is to motivate playing by helping players understand how they can perform better in the game. As players improve in an educational game, they are implicitly learning and improving in the areas targeted by the game. Thus, supporting higher in-game performance translates into supporting learning. In such environments, players are playing the game for enjoyment and not necessarily for learning. Therefore, the players might appreciate information about how to improve their in-game performance more than an assessment report of their learning progress.

The learning analytics dashboard introduced in this chapter also has been designed for the inclusion of learning analytics rather than adding existing learning analytics tools or features afterwards. As such, it benefits from using a wide variety of data to provide players with game-specific information on their performance and play habits as well as allows them to create their own custom visualizations to analyze their performance and play habits.

3 Overview of Game

The educational game designed by the research team is aiming to improve players' metacognitive skills. Metacognition is the understanding of a person's own cognition and thought processes [15]. The game targets four skills that are essential to metacognition: (1) problem solving, (2) associative reasoning, (3) organization and planning, and (4) monitoring/checking work for accuracy.

The game has ten subgames and each of them targets the improvement of a metacognitive skill. Players are playing matches against other players. In each match, players are playing three subgames and both players are scored by how they performed individually and against their opponent. For each subgame played, a performance score is calculated that shows how well the player played that subgame. The player is also compared to their opponent by adding up the performance score for each of the three subgames they played in a match. The player with the highest sum of performance scores is the declared winner of the match. The winner receives points and the loser loses points, which allow players to be ranked against other players based on game performance. There is no limit to how many matches a player can play in a play session. A play session is defined from when a player logs into the game to when they log out or are inactive for ten minutes.

A metacognitive skill score in a subgame is calculated based on the performance score as a percentage value compared to the highest possible performance a player can get. The score represents the metacognitive skill level reached in the subgame. The player's overall score for a particular metacognitive skill comes from the highest scores in all subgames associated with the same metacognitive skill.

Besides the points players get for winning a match, several other motivational features have been included in the game to encourage players to continue playing. Players can unlock 48 badges that are linked to game activities, such as logging in for consecutive days in a row, winning matches, and using the learning analytics dashboard. Players can also earn currency every time they play a match, which they can then use to upgrade a robot avatar that represents them in the game. The game also features a leaderboard that can rank players against each other. As mentioned, players can be ranked by points, but additionally, player can be ranked on the leaderboard by other metrics, such as their metacognitive skill score, or how much currency they have.

4 Learning Analytics Dashboard

The purpose of the learning analytics dashboard is to show players how they can improve their performance in subgames, and consequently, improve their metacognitive skills. A variety of information is tracked about players for the learning analytics dashboard. This information includes, when players start and end a play session; when players start and end a match, when players start and end a subgame; which subgames players played; which metacognitive skill is associated with the subgames played; how the players performed in subgames; and the players metacognitive skill score after a subgame played. This information can be used to determine how often players login, how long they play, how many matches they play in a play session, what time in a day they usually play, how they performed in a subgame, and how their metacognitive skill score changes after playing a subgame.

There are two charts that have been adopted by the proposed learning analytics dashboard: (1) line graphs, which visualize metacognitive skill scores; and (2) scatter plots, which visualize the performance scores. The dashboard also offers players (1) a "Brain" tab, which visualizes metacognitive skills; and, (2) a "Game" tab, which visualizes performance in subgames (see Fig. 1).

Through the "Brain" tab, a player can select which metacognitive skills (i.e., a single skill or a group of skills) he or she wants to see and in the "Game" tab, the player can select which subgames (i.e., a single subgame or a group of subgames) performance should be displayed so he or she can check it out. In addition, in the "Brain" tab, each metacognitive skill can be exploded to show the performance scores of the subgames related to the respective metacognitive skill. The purpose of the exploded view is to demonstrate how subgame performances impact the player's metacognitive skill score. Moreover, players can filter based on a time frame using a sliding time frame bar so they can focus on the visualized data within a particular time frame.

The line graphs (in Fig. 1) visualize a player's scores over time to show how the player has improved. The player can check their improvement over days, play sessions, or matches played. Seeing the growth over days can give players a general overview of how they have improved over time; seeing the growth over play sessions or matches can give them more details about how they improved when they have multiple play sessions in a day or multiple matches in a play session.

While the "Brain" tab allows players to see the improvement for each metacognitive skill, at subgame level (i.e., either in the "Game" tab or when a metacognitive

Fig. 1 Line graph of metacognitive skills improvement with problem-solving exploded

skill is exploded in the "Brain" tab), the actual metacognitive skill scores in the particular subgame is shown, providing more details about how well a player did in those particular subgames. For example, Fig. 1 shows such a chart with the problem-solving skill exploded and the other three skills displayed, but not exploded. The metacognitive skills that are not exploded show one line each visualizing how the player's skill has changed over three months. Whereas, problem-solving instead has two lines, one line for each subgame that contributes to the calculation of the player's problem-solving score. The subgame lines are red to show that they are associated with problem-solving, but have different line dash patterns so that they can be distinguished from each other.

The scatter plot visualizations focus on showing how performance is affected by playing habits. There are two views: performance by time in a day and performance by matches played in a session. The first view (as shown in Fig. 2) displays how the player performed per metacognitive skill or subgame at different times of the day. The x-axis is the time of day a subgame was played and the y-axis is the performance player got playing the subgame. The purpose of this visualization is to help a player identify if they perform better at different time of a day.

For example, Fig. 2 shows a visualization of a player that has played problem-solving subgames between 8:00 am and 10:00 pm over three months. Points that are close horizontally, represent subgames that were played around same time of day. When grouping subgames by metacognitive skill in the scatter plot, points for the same metacognitive skill are drawn in the same color, but different shapes are used for different subgames. Because both subgames 1 and 2 are associated with

Fig. 2 A scatter plot depicting a player performing better in the evening

problem-solving skill, the points have two shapes: circle for subgame 1 and triangle for subgame 2. Both points are red to show that both are associated with problem-solving.

The second view of the scatter plots (see Fig. 3) shows how performance changes over multiple matches played in a play session. The *x*-axis shows the time and day the session took place. The *y*-axis shows when the subgame was played within the session (in minutes), with 0 on the *y*-axis representing the start of the session. Each point represents the player playing a subgame during a play session. Points that are line up vertically represent a play session. The color of the point indicates the performance of the player had in that subgame—a darker color indicating higher performance and a lighter color indicating lower performance. The purpose of the visualization is to show if a player's performance changes by playing multiple subgames in one session.

In Fig. 3, for example, we can see that in the first session on January 18th, three subgames were played. The three points are light because the player had their lowest performances in those games within the time frame that was selected on the bottom of the screen with the time frame bar. Conversely, the last three subgames in the last session on January 23rd have a dark green colored points indicating that the player had their highest performance in those subgames within the selected time frame.

Fig. 3 Scatter plot of subgame performance by matches played in session

5 Proof of Concept Evaluation

The purpose of the proof of concept evaluation is to verify whether the learning analytics dashboard can give players meaningful information about how they can improve their in-game performance. Three months of simulated gameplay data were created. The evaluation uses four use cases to evaluate the resulting visualizations and to explain how they benefit players. The four use cases include: (1) a player not performing well in one of the four metacognitive skills, (2) a player that plays sometimes very often and sometimes rarely, (3) a player that performs better at a certain time of a day, and (4) a player whose performance increases after re-familiarizing themselves with the game.

Metacognitive skills from one area do not necessarily translate to the others [16]. Therefore, first use case deals with visualizing a player that is lower in one of the four metacognitive skill areas. Figure 1 depicts a line graph that displays a player's metacognitive skills over time. The depicted player has lower scores in games that target problem-solving. The problem-solving skill line is exploded to show that subgame 1 and 2 contribute to the skill score. The player can use this information to determine that he or she needs to develop strategies to improve his or her performance in subgame 1 and 2. Showing the player that both subgames target the same metacognitive skill will also indicate that strategies that work in one game could apply to the other.

Skill development is dependent on many factors, but an important element is regular practice [17]. The second use case demonstrates how the connection between regular practice and high performance can be visualized and noticed by players. Figure 4 depicts a player that plays subgame 8 only a few times in November, then plays it frequently in the month of December, and then infrequently again in January. Although his or her skill improves across the three months, there is a greater improvement in the month where he or she plays often and less improvement in the months where the player plays only a few times. This shows him or her that if he or she wants to improve his or her in-game performance faster, he or she should play the game often rather than erratically.

Performance on some types of cognitive tasks, such as those associated with metacognitive skills, can be varied by time of day [18]. Figure 5 shows the scatter plot which visualizes the player's performance in subgame 5 by the time of day it was played. When he or she is looking at this chart, he or she can see that his or her performance is relatively low in the morning and during the day, and increases towards the evening. Therefore, this chart can help a player to identify which times are better for him or her to play the game. For example, if this player identified that he or she needs to improve his or her Planning and Organization skill and subgame 5 is associated to the skill (according to the dashboard shown in Fig. 1). Figure 5 shows the player that he or she may improve their score by increasing the number of subgames played in the evening.

Performance in cognitive tasks is influenced by familiarity with the task [19]. Players may perform poorly at cognitive task in the beginning or after a longer

Fig. 4 A line graph depicting a player that played less in November and January but more in

Fig. 5 A scatter plot depicting a player that performs better in the evening

break, not because they are unskilled, but because they are unsure about what they need to do. In the context of the game designed by the research team, this could mean that a player might need to warm-up by playing multiple matches and subgames in one play session.

The last use case deals with a visualization of a player who performs better after they have played a few matches to re-familiarize themselves with the subgames. In Fig. 3 the chart depicts a scatter plot of performances in subgame 3 based on how many games were played in a play session. The player's performance increases consistently within a play session, which can be seen by how the points become darker in a session. Between frequent play sessions, the darkness of the points in the beginning of a new session is similar in darkness to the points at the end of the previous session, which indicates that the player performance remains stable between short breaks in play. However, after a longer lapse in play, such as the gap between January 19th and 22nd, the points become much lighter indicating a dropping performance.

Seeing the performance of subgames played in the same session can help players identify if they need to play more games after an absence to re-familiarize themselves with the subgames as well as how their performance changes in sessions with multiple subgames. For example, a player could use this dashboard in tandem with the one featured in Fig. 4 to identify if a plateau in performance could be overcome by playing more subgames in one play session.

6 Conclusion

This chapter presented how to adopt learning analytics into an educational game. The proposed learning analytics dashboard provides a way for players to see and analyze their game play habits and allows them to understand how those habits may affect their in-game performance. With the dashboard, players can be made aware of how to improve their in-game performance. The designed dashboard was evaluated through a proof of concept evaluation with a 3-month gameplay simulated dataset by considering four use cases. The evaluation showed that the dashboard can provide players with meaningful feedback about how their play habits affect their in-game performance and with a useful tool to build strategies to improve their in-game performance.

Future work will focus on players' perceived usability and acceptance toward the learning analytics dashboard. The research team also plans to investigate how players use the dashboard while playing, and if their play habits change after using the dashboard. Players' acceptance of the dashboard will be explored by analyzing players' usage rates and by administering questionnaires to collect their self-reported satisfaction towards the dashboard. The collected data will be analyzed with statistical approaches.

References

1. Gee, J. P. (2013). *Good video games + good learning* (2nd ed.). New York: Peter Lang Publishing.
2. Song, M., & Zhang, S. (2008). EFM: A model for educational game design. In *Technologies for e-learning and digital entertainment* (pp. 509–517).
3. Wouters, P., Van Nimwegen, C., Van Oostendorp, H., & Der Spek, E. D. (2013, February). A meta-analysis of the cognitive and motivational effects of serious games. *The Journal of Educational Psychology*, 1–17 (Advance Online Publication).
4. Wang, A. I. (2015, March). The wear out effect of a game-based student response system. *Computers and Edcuation, 82*, 217–227.
5. Keller, J. M. (1987). Strategies for stimulating the motivation to learn. *Performance Improvement, 26*(8), 1–7.
6. Hauge, J. B., Manjón, B. F., Berta, R., Padrón-Nápoles, C., Giucci, G., Westera, W., et al. (2014, July). Implications of learning analytics for serious game design. In *Proceedings of IEEE 14th International Conference on Advanced Learning Technologies (ICALT)* (pp. 230–232). IEEE.
7. Loh, C. S. (2013, January). Improving the impact and return of investment of game-based learning. *The International Journal of Virtual and Personal Learning Environments,4*(1), 1–15.
8. Alonso-Fernandez, C., Calvo, A., Freire, M., Martinez-Ortiz, I., & Fernandez-Manjon, B. (2017, April). Systematizing game learning analytics for serious games. In *Proceedings of Global Engineering Education Conference (EDUCON)* (pp. 1106–1113). IEEE.
9. Malliarakis, C., Satratzemi, M., & Xinogalos, S. (2014, July). Integrating learning analytics in an educational MMORPG for computer programming. In *Proceedings of IEEE 14th International Conference on Advanced Learning Technologies (ICALT)* (pp. 233–237). IEEE.
10. Serrano-Laguna, A, Torrente, J., Moreno-Ger, P., & Manjón, F. B. (2012, December). Tracing a little for big improvements: Application of learning analytics and videogames for student assessment. *Procedia Computer Science, 15*, 203–209.
11. Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017, February). Applying standards to systematize learning analytics in serious games. *Computer Standards and Interfaces, 50*, 116–123.
12. Loh, C. S. (2012). Information trails: In-process assessment of game-based learning. In *Assessment in Game-Based Learning: Foundations, Innovations, and Perspectives* (Chap. 8, pp. 123–144). New York: Springer Science + Business Media.
13. Loh, C. S., Anantachai, A., Byun, J., & Lenox, J. (2007, July). Assessing what players learn in serious games: In situ data collected, information trails, and quantitative analysis. In *Proceedings of 10th International Conference for Computer Games: AI, Animation, Mobile, Education & Serious Games (CGAMES 2007)* (pp. 25–28).
14. Freire, M., del Blanco, Á., & Fernández-Manjón, B. (2014, April). Serious games as edX MOOC activities. In *Proceedings of Global Engineering Education Conference (EDUCON)* (pp. 867–871). IEEE.
15. Flavell, J. H. (1979, October). Metacognition and cognitive monitoring: A new area of cognitive-developmental inquiry. *American Psychologist, 34*(10), 906–911.
16. Schraw, G. (1998, March). Promoting general metacognitive awareness. *Instructional Science, 26*, 113–125.
17. Ericsson, K. A. (2006). The influence of experience and deliberate practice on the development of superior expert performance. In *The Cambridge handbook of expertise and expert performance* (pp. 685–705).
18. Goldstein, D., Hahn, C. S., Hasher, L., Wiprzycka, U. J., & Zelazo, P. D. (2018, January). Time of day, intellectual performance, and behavioral problems in morning versus evening type adolescents: Is there a Synchrony effect? *Personality and Individual Differences, 42*(3), 431–440.
19. Collie, A., Maruff, P., Darby, D. G., & McStephen, M. (2003, March). The effects of practice on the cognitive test performance of neurologically normal individuals assessed at brief test-retest intervals. *The Journal of the International Neuropsychological Society, 9*, 419–428.