

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

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24 players with information, but problems for them to solve [1]. Part of what makes a
25 game fun is that the in-game problems are challenging [1]. By framing a learning
26 objective around such a challenge, it can be integrated into a game in a fun way.
27 In this way, an educational game allows the player to learn by playing. Learning is
28 implicit from the feedback they receive about the actions they have taken or choices
29 they have made in the game [2].

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

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

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

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

65 2 Related Works

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

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

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

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

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

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

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

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

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

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

145 3 Overview of Game

146 The educational game designed by the research team is aiming to improve players'
147 metacognitive skills. Metacognition is the understanding of a person's own cogni-
148 tion and thought processes [15]. The game targets four skills that are essential to

149 metacognition: (1) problem solving, (2) associative reasoning, (3) organization and
150 planning, and (4) monitoring/checking work for accuracy.

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

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

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

178 4 Learning Analytics Dashboard

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

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

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

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

211 While the “Brain” tab allows players to see the improvement for each metacog-
 212 nitive 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

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

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

230 For example, Fig. 2 shows a visualization of a player that has played problem-
 231 solving subgames between 8:00 am and 10:00 pm over three months. Points that
 232 are close horizontally, represent subgames that were played around same time of
 233 day. When grouping subgames by metacognitive skill in the scatter plot, points for
 234 the same metacognitive skill are drawn in the same color, but different shapes are
 235 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

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

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

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



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

255 5 Proof of Concept Evaluation

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

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

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

285 Performance on some types of cognitive tasks, such as those associated with
286 metacognitive skills, can be varied by time of day [18]. Figure 5 shows the scatter
287 plot which visualizes the player's performance in subgame 5 by the time of day it
288 was played. When he or she is looking at this chart, he or she can see that his or
289 her performance is relatively low in the morning and during the day, and increases
290 towards the evening. Therefore, this chart can help a player to identify which times
291 are better for him or her to play the game. For example, if this player identified that
292 he or she needs to improve his or her Planning and Organization skill and subgame
293 5 is associated to the skill (according to the dashboard shown in Fig. 1). Figure 5
294 shows the player that he or she may improve their score by increasing the number of
295 subgames played in the evening.

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

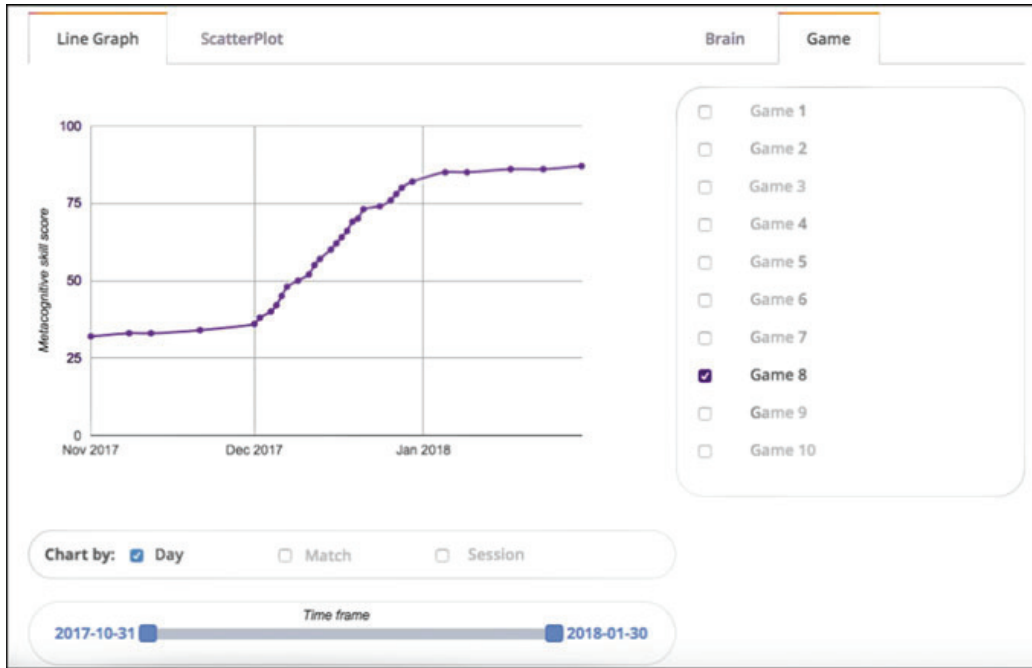


Fig. 4 A line graph depicting a player that played less in November and January but more in

Editor Proof



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

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

302 The last use case deals with a visualization of a player who performs better after
303 they have played a few matches to re-familiarize themselves with the subgames.
304 In Fig. 3 the chart depicts a scatter plot of performances in subgame 3 based on
305 how many games were played in a play session. The player's performance increases
306 consistently within a play session, which can be seen by how the points become
307 darker in a session. Between frequent play sessions, the darkness of the points in the
308 beginning of a new session is similar in darkness to the points at the end of the previous
309 session, which indicates that the player performance remains stable between short
310 breaks in play. However, after a longer lapse in play, such as the gap between January
311 19th and 22nd, the points become much lighter indicating a dropping performance.

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

318 6 Conclusion

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

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

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