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25 Data Analytics Approaches
26 in Educational Games
27 and Gamification Systems
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Chapter 13

Data Analytics Approaches in Educational Games and Gamification Systems: Summary, Challenges, and Future Insights



Ahmed Tlili and Maiga Chang

Abstract This chapter summarizes the reported findings of this book to facilitate the adoption of data analytics in educational games and gamification systems. Specifically, this chapter presents the objectives of adopting data analytics which is finding individual differences; doing learning assessments and knowing more about the learners. It then presents the collected metrics and applied analytics techniques in order to achieve these objectives. Additionally, this chapter highlights several limitations reported by other authors during the adoption of learning analytics. These limitations should be considered by researchers and practitioners in their context to facilitate learning analytics adoption. Finally, this chapter provides future insights about the learning analytics field.

1 Objectives of Adopting Data Analytics

The inclusion of data analytics within educational games and gamification systems can make them smart by achieving several objectives, highlighted in this book, as follows:

- **Finding individual differences:** Traditional learner modeling instruments, such as questionnaires, have been reported to be lengthy and not motivating. With the help of data analytics, a system includes educational game is capable of modeling learners implicitly. Furthermore, individual differences like competences (computational thinking in particular) and motivation can also be found (see Chaps. 11 and 12 for more details). The modeling process is considered a crucial step in order to provide personalized and adaptive learning services based on individual differences that are further highlighted in this chapter).

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249



- 23 ● **Do learning assessments:** In online learning environments like MOOCs, mas-
24 sively multiplayer educational games, where thousands of learners are taking their
25 pace for studying and doing learning activities. It becomes very difficult for teach-
26 ers to monitor learners' learning progress, assess learners' skills and knowledge
27 levels, and take care of individual needs. Data analytics have been applied to solve
28 this issue and help teachers. For instance, Tlili and his colleagues develop iMoodle
29 that can identify at-risk students and provide them personalized learning support
30 (see Chap. 6). With data analytics' help, the completion rate of a course can also
31 be improved. Seaton and her colleagues provide learning analytics dashboard for
32 the learners so they can easily keep track of their progress, realize their habits and
33 weaknesses to help them overcome obstacles and achieve better learning outcome
34 (see Chap. 7).
- 35 ● **Know more about the learners:** Traditional educational games and gamifica-
36 tion systems are black boxes where teachers cannot see or know, besides the final
37 scores and levels cleared, how their learners do in the learning process and behave
38 towards the learning goal. Data analytics approaches have been applied to over-
39 come this limitation. Ifenthaler and Gibson explore the learning engagement and
40 its relationship with learning performance in the context of game-based learning
41 (see Chap. 3). Also, Shute, Rahimi, and Smith explore the importance of including
42 learning supports and its impact on learning performance when using the Physics
43 Playground game (see Chap. 4).

44 Based on the reported chapters in this book, Fig. 1 presents a generic framework of
45 adopting data analytics in educational games and gamification systems to achieve the
46 three objectives mentioned above. When learners use and interact with the developed
47 educational game or gamified system, several metrics (traces) are created based on
48 the interactions and collected into the database. The data analytics module(s) is (are)
49 developed either as the built-in the game and system or accessories of the game and
50 system. The module takes the collected metrics as inputs and does proper analysis
51 and produce results as outputs for achieving a particular objective.

52 It should be noted that no chapter reports the use of cloud computing technology
53 to store the collected metrics. Also, no chapter has parents, as stakeholders, for
54 the application of data analytics in educational games and gamification systems.
55 Therefore, further investigation is needed regarding these two matters.

56 2 Collectable Metrics and Traces

57 It has been seen that the more data is collected within educational games and gamifi-
58 cation systems, the more possibilities we will have to enhance the learning process.
59 Kinshuk et al. [1] highlight that to provide smart learning every bit of information
60 that each learner comes into contact with should be collected. For example, to predict
61 at-risk students, Tlili and his colleagues in Chap. 6 use the following five metrics,
62 namely: (1) Number of acquired badges which highlights the number of conducted

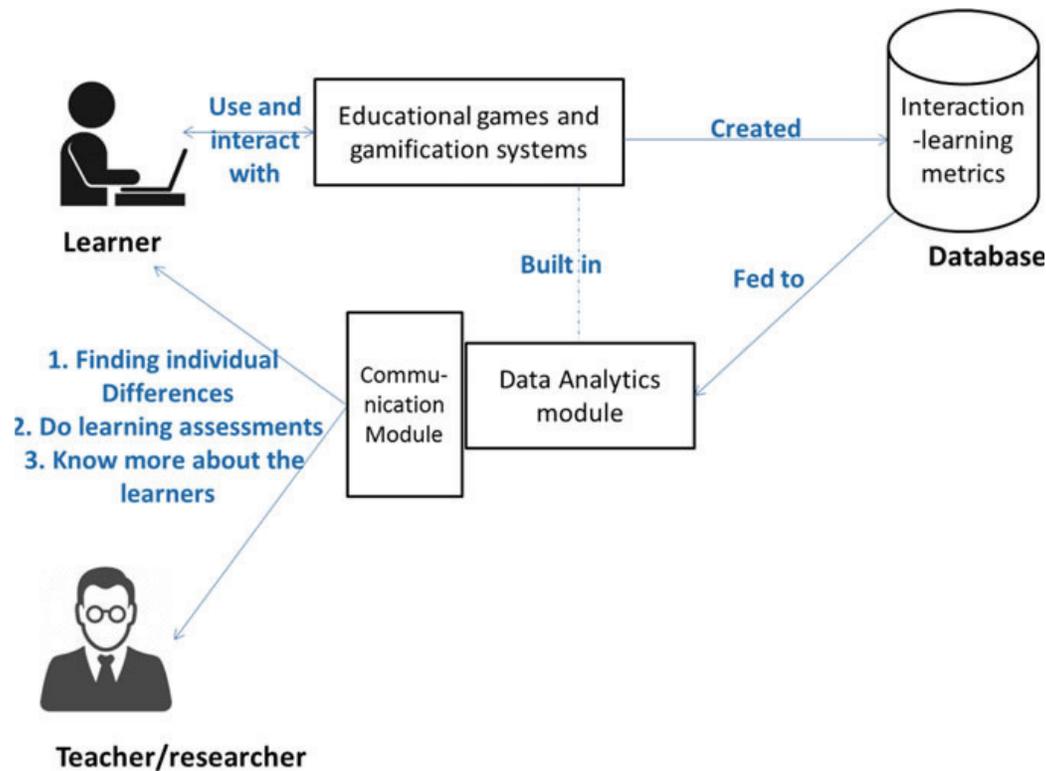


Fig. 1 Generic process of adopting data analytics in educational games and gamification systems

63 learning activities, since every time a student finishes a learning activity, he/she gets
 64 a badge; (2) Activities grades which refer to the value assigned by teachers to assign-
 65 ments and quizzes requested and delivered by students; (3) Student's rank on the
 66 leaderboard which is based on the acquired number of points (4) Course progress
 67 which can be seen in the progress bar; and, (5) Forum and chat interactions which
 68 refers to students' participation in online discussions, such as the number of posts
 69 read, posts created and replies.

70 To identify the motivation of students in an educational game, Flores, Silverio,
 71 Feria, and Cariaga use in Chap. 12 the following five metrics, namely: (1) diffi-
 72 culty versus accuracy: compared to assess students' behavior; the student's choice of
 73 difficulty based on their result in the previous problem (correct, wrong or skip); (2)
 74 number of non-easy problems chosen: the total number of selected medium, hard and
 75 expert difficulty problems; (3) number of non-skipped problems: measured to give
 76 students a reasonable score for this metric as skipping is generally considered a neg-
 77 ative factor; (4) accuracy versus time: were also compared to identify students who
 78 only guess the answers; and, (5) perks versus accuracy: were compared to examine
 79 students' engagement or mastery in solving a problem.

80 To assess computational thinking skills, Montañó, Mondragón, Tobar-Muñoz, and
 81 Orozco use in Chap. 5 the following seven metrics, namely, (1) abstraction and pattern
 82 recognition: focus on not having unused code, the use of functions in the code, and the
 83 use of clones of blocks of code (a specific functionality of the Scratch environment);

84 (2) flow control: assessment of the correct use of every control instruction (such as if
 85 and for statements), and also the adequate use in nesting those statements; (3) input
 86 control: assessment of the adequate use of statements designed to capture user input
 87 into the code, the naming of variables, and the use of non-user-defined variables; (4)
 88 data analysis: assessment of the treatment and transformation of the data through the
 89 use of data transformation blocks or statements, and also their adequate nesting if
 90 necessary; (5) parallelism and threading: assessment of the adequate use of threading
 91 and multi-tasking enabling blocks; (6) problem-solving: assessment of the student's
 92 ability to decompose a problem into multiple smaller ones in order to address them
 93 more easily; and, (7) algorithmic thinking: assessment of the student's ability to
 94 develop sequences of tasks, that would be translated into blocks of code, in order to
 95 solve a problem.

96 While Ghergulescu and Muntean [2] mentioned that little is known about the
 97 collected traces and used metrics in game-based learning environments, it has been
 98 seen that different types of metrics could be collected by asking three questions as
 99 Fig. 2 shows:

- 100 (1) *What types of metrics should be collected?* Two types of metrics (traces) can be
 101 collected, namely, (1) generic metrics which can be found in most educational
 102 games and gamification systems, such as the number of signing into an educa-
 103 tional game or gamification system, and the time spent on the game or system;
 104 and, (2) specific metrics which are defined based on the designed learning envi-

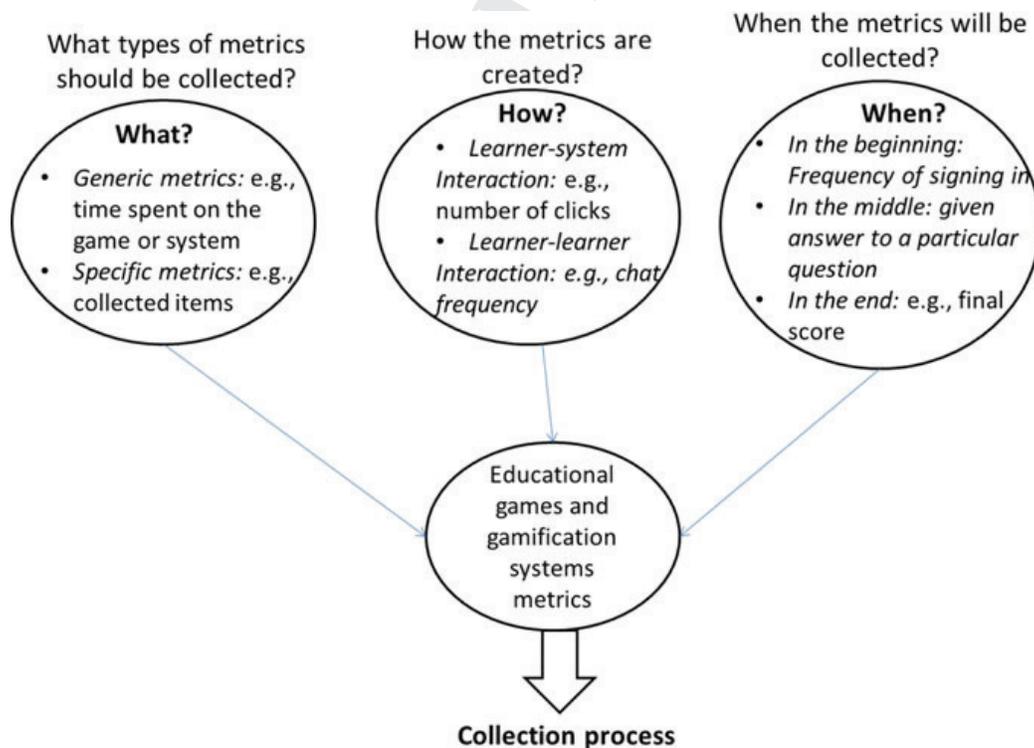


Fig. 2 Types of collected metrics in educational games and gamification systems

105 environment, such as number of collected items (badges, points, coins, etc.) and the
106 selected game path.

107 (2) *How the metrics are created?* One kind of metrics (traces) is created when the
108 learners interact with the educational game or the gamification system, while
109 the others can be created when the learners are interacting with others within
110 the game or the system. For instance, chat frequency is created when learners
111 start to chat together within the game or the system to solve a particular learning
112 activity.

113 (3) *When the metrics will be collected?* Metrics (traces) can be collected at the
114 beginning, in the middle or at the end of the game-play or the usage of the
115 gamification system. For instance, the final score is collected at the end while the
116 number of times to sign in the game or the system is collected at the beginning.

117 To extract useful information from the collected metrics (discussed above), dif-
118 ferent analytics techniques are applied, as discussed in the next section.

119 3 Analytics Techniques

120 Based on the chapters included in this book, three analytics techniques are usually
121 adopted in educational games and gamification systems:

- 122 • *Data Visualization*: It uses visualization such as pie charts and histograms to
123 represent data. This can help to communicate information clearly and efficiently
124 to stakeholders (e.g., teachers, students, etc.). For instance, the authors in Chaps. 6
125 and 7 all adopt data visualization techniques to create dashboards for both teachers
126 and students.
- 127 • *Data Mining*: It aims to discover hidden information and meaningful patterns from
128 massive data. In this context, several algorithms are adopted. For example, Tili and
129 his colleagues in Chap. 6 adopt association rules mining and Apriori Algorithm
130 to predict at-risk students.
- 131 • *Sequential Analysis*: It allows exploring, summarizing, and statistically test cross-
132 dependencies between behaviors that occur in interactive sequences. For example,
133 Moon and Liu in Chap. 2 conduct a systematic literature review on 102 articles
134 that work on sequential data analytics (SDA) in game-based learning.

135 Several studies also reported the abovementioned analytics techniques are com-
136 monly adopted in games [3–5]. Several challenges, on the other hand, are reported
137 by the authors, in their chapters, which might hinder the adoption of data analytics
138 in educational games and gamification systems. These challenges are discussed in
139 the next section.

140 4 Challenges

141 Based on the chapters included in this book, several challenges are reported by the
142 authors. These challenges should be considered by researchers and practitioners in
143 their context to enhance the adoption of data analytics in educational games and
144 gamification systems.

145 Moon and Liu in Chap. 2 highlight two limitations while adopting data analytics
146 approaches, specifically sequential analysis, in educational games and gamification
147 systems, namely: (1) the need for high computational power in order to collect
148 and analyze big data; and, (2) sequential analysis is often performed as post hoc
149 analysis. Therefore, it is challenging to ensure the validity of the results without
150 cross-validating with the participants. In addition, the participants may not even recall
151 some certain behaviors because the data is captured at a fine granularity. Another
152 issue with post hoc analysis is if the scope of the study is biased, data collection will
153 be biased which in turn leads to an invalidated biased results.

154 Ifenthaler and Gibson in Chap. 3 and Montaña, Mondragón, Tobar-Muñoz, and
155 Orozco in Chap. 5 report that one of the challenges is collecting large enough data
156 so the applied data analytics approach within their gamified systems can be more
157 accurate. Tlili and his colleagues in Chap. 6 highlight the challenge of protecting
158 learners' privacy while applying educational games and gamification systems. They
159 also discuss the importance of having a predefined time of keeping the learners'
160 stored data.

161 5 Conclusion

162 Game-based learning environments and learning analytics are gaining increasing
163 attention from researchers and educators since they both can enhance learning out-
164 comes. Therefore, this book covered a hot topic which is the application of data
165 analytics approaches and research on human behavior analysis in game-based learn-
166 ing environments, namely educational games and gamification systems, to provide
167 smart learning. Specifically, this book discussed the purposes, advantages, and limi-
168 tations of applying these analytics approaches in these environments. Additionally,
169 this book helped readers, through various presented smart game-based learning envi-
170 ronments, integrate learning analytics in their educational games and gamification
171 systems to, for instance, assess and model students (e.g., their computational think-
172 ing) or enhance the learning process for better outcomes. Finally, this book presented
173 general guidelines, from different perspectives, namely, collected metrics, applied
174 algorithms and the encountered challenges during the application of data analytics
175 approaches, which facilitate incorporating learning analytics in educational games
176 and gamification systems.

177 Future directions for readers to consider and focus could be: (1) investigating the
178 use of data analytics in educational games and gamification systems for health educa-

179 tion in particular; and, (2) investigating how Internet of Things (IoT), which is a new
180 technology that is gaining increasing attention from researchers and practitioners,
181 could help the application of data analytics in educational games and gamification
182 systems.

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