Data Mining Techniques for Analysing Data Extracted from Serious Games: A Systematic Literature Review

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Abstract: Serious games are applications that pursue, on the one hand, the users' entertainment and, on the other hand, look to promote their learning, cognitive stimulation, among reaching other objectives. Moreover, data generated from those games (e.g., demographic information, gaming precision, user efficiency) provide insights helpful in improving certain aspects such as the attention and memory of the gamers. Therefore, applying data mining techniques over those data allows obtaining multiple patterns to improve the game interface, identify preferences, discover, predict, train, and stimulate the users' cognitive situation, among other aspects, to reach the games' objectives. Unfortunately, although several solutions have been addressed about this topic, no secondary studies have been found to condensate research that uses data mining to extract patterns from serious games. Thus, this paper presents a Systematic Literature Review (SLR) to extract such evidence from studies reported between 2001 and 2021. Besides, this SLR aims to answer research questions involving serious games solutions that train the cognitive functions of their users and data mining techniques associated with data gathered from those games.

1 INTRODUCTION

Serious games are defined as software applications developed for an explicit educational purpose (Hernández et al., 2017). Moreover, the objective of these games is not primarily intended for fun but is focused on government or corporate training, education, health, public policy, and strategic communication purpose (Hernández et al., 2017). Moreover, serious games are developed to include interactive and engaging features. These features can be collected, extracted, measured, analyzed, and reported. Gathered data can consider users' attributes and behavior, the learning progress, and other outcomes (Chen et al., 2020; Shoukry et al., 2014).

To process the collected data, the Data Science field can be applied; here, data mining is the branch that uses a computer-based methodology that helps to discover knowledge (Mendoza et al., 2019). Different techniques are performed in the data mining field, including classification, regression, clustering, summarization, association, and anomaly detection (Petrov et al., 2019).

Here, the classification automatically assigns a pre-defined category to each variable based on its attributes (Petrov et al., 2019; Zanasi & Ruini, 2018). While clustering automatically creates clusters of variables that share similar characteristics (Petrov et al., 2019; Zanasi & Ruini, 2018).

Some of these techniques have been implemented in the area of serious games. For example, Ruiz-Rube et al. (2013) present two serious games: i) a memory game that seeks to match photos with audio and text; ii) a hidden room where the player must situate objects in their place. Their research aims to apply the k-means algorithm to detect behavior and preferences according to the user profile. Clustering techniques are used, and the results identify errors in the lexicon with different degrees (low, medium, good). Another example is a serious game called Enzyme-Linked Immunosorbent Assay (ELISA), developed by Simani et al. (2018), whose main contribution is the

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detection of Human Immunodeficiency Viruses (HIV) through an analysis of peptides, proteins, antibodies, and hormones. Besides, Benmarkelouf et al. (2015) implemented a regression and clustering model to explore the relationships between the characteristics of the players and their performance (scores and duration of the game). Features such as personalization, the existence of groups of players, and the identification of their characteristics to extract players' profiles, were available.

From the previous studies, it can be seen that there are different data mining techniques implemented in many areas of knowledge. Thus, several primary studies have been reported. However, those contributions are scattered in many scientific sources. Therefore, it is necessary to search for them when new research starts and state of the art must be established. Consequently, this paper presents a review that summarizes the most used and implemented data mining techniques, the domain area where the serious game is developed, and the collected users' demographic information is needed. This study follows the methodology proposed by Kitchenham et al. (2010) for systematic literature reviews. A systematic literature review (SLR) is a document that presents a summary of the most relevant studies referred to a particular research question (Kitchenham et al., 2010). Several steps are proposed in this methodology, making the process repeatable and auditable.

The obtained results aim to answer "*How research on data science solutions applied to serious games is taking place,"* the research emphasizes data mining techniques. Following the suggested methodology, 60 studies were selected and analyzed. Finally, results provide insights helpful to find gaps and support researchers in this area.

This paper is organized as follows: Section 2 presents an analysis of the related systematic reviews in serious games and data mining. Then, Section 3 shows the research method implemented in this review. Section 4 presents the discussion about the reviewed literature, while Section 5 includes threats to validity and their mitigation. Finally, Section 6 concludes the paper and offers the guidelines for future work.

2 RELATED WORKS

For this review, the main research question focuses on how data science solutions are applied to data extracted from serious games. Four reviews related to this topic were found, but none thoroughly addressed our research question.

Thus, Alonso-Fernández et al. (2019) presented a systematic literature review that includes data science applications to perform game and learning analytics with data collected from serious games. However, the original search string did not explicitly have "serious games"; besides, the authors used three different search strings. Their study concluded with a summary of the purpose of data analysis application of the studies and the data science techniques used in the selected articles. They also presented a table with the algorithms and procedures generally, only mentioning the concepts but not a specific number of studies implemented.

Massa & Küh (2018) present a review based on the methodology proposed by Kitchenham (2010). Their study is oriented to data analytics in serious games. It aims to identify the solutions on learning analytics, the type of serious game (commercial or non-commercial), and the methodologies and tools for implementing learning analytics. However, their main research question was related to learning analytics, fun, and implementations. Although the review was based on serious games, it did not include any topic related to data science, such as: methodologies, algorithms, or techniques. Besides, it only addresses the benefits of integrating "big data" into the solution, but the authors do not emphasize the process. Then, in a systematic review, Ravyse et al. (2017) analyzed the success factors that enhance learning when applying serious games. The authors focused on presenting the practical guidelines that serious game producers could incorporate to guarantee successful learning with fun. Among those are the plot, the narrative of the game, the audio-visual techniques, and graphics. In addition, the work presented which artificial intelligence techniques are used to improve fun and learning experiences and convert player information into personalized responses but did not include an explanation of the types of methods used.

Finally, Wang & Huang (2021) developed a systematic review of the design of serious games for collaborative learning. The design aspect is the most relevant topic analyzed. They indicated that few studies had implemented a data mining method on game logs, but they did not present details about it.

Although there are some similarities between the previously described contributions and this systematic literature review, the main difference is that this study is mainly focused on how serious games are addressed in data science, considering the methodology, algorithms, game mode, and data storage. Besides, this review includes demographic users' information, such as age, score, and interaction. Another significant difference relies on the libraries and indexers selected to extract scientific articles and the search strategy.

3 RESEARCH METHOD

According to Kitchenham (2010), an SLR consists of collecting, organizing, evaluating, and interpreting the information related to a specific Research Question (RQ) about an area or phenomenon of interest. Then, Kitchenham proposes a methodology based on three steps: 1) Planning the SLR, 2) Conducting the SLR, 3) Reporting the results.

3.1 Planning the SLR

The planning stage consists of establishing the research questions and sub-questions, the search strategy, the selection of primary and secondary studies, and its extraction criteria. Also, it includes a quality assessment procedure to validate the review.

3.1.1 Research Questions

Research questions are the most relevant part of the SLR. They allow finding relevant data and transforming the systematic literature review into a contribution to the research (Kitchenham et al., 2010). Here, two main aspects have been considered: serious games and data science.

The terms "learning analytics", "data mining" and "big data" were also included. Learning analytics and educational data mining sometimes are used interchangeably (Alonso-Fernández et al., 2019), while "big data" refers to data sets whose size and/or complexity can be effectively exploited by using data science techniques (Zanasi & Ruini, 2018).

The main question is "how research on data science solutions applied to serious games is taking place". The four research sub-questions are: RQ1: What kind of information is required to analyze serious games? RQ2: How are serious games approached in data science? RQ3: In which development area are serious games applied? RQ4 How is the investigation and its scope?

3.1.2 Search Process

It is necessary to select the sources to obtain the articles to be considered for this review. Therefore, international conferences about serious games, digital libraries, and indexed electronic databases were considered. Those are ACM-Digital Library, IEEE Xplore, Springer Link, Science Direct, EBSCO, Taylor & Francis, Hinari (OARE), Web of Science, and SCOPUS. Likewise, three international conferences were included: International Conference on Serious Games and Game-Based Learning, International Conference on Serious Games and Applications for Health, and International Conference on Gamification & Serious Game.

The search string was developed using four groups of keywords according to the research scope. Groups of keywords were defined as "data science", "big data", "data mining" and "serious games." The final string used in the search engines was ("Data mining OR "Big data" OR "Data Science") AND ("serious games"). The considered period of the publications was from the first peer-reviewed academic journal dedicated to computer game studies, published in 2001 (Wilkinson, 2016).

3.1.3 Exclusion and Inclusion Criteria

A process of selection was applied to the obtained articles. It included a preliminary reading of the title, keywords, and the abstract of each piece to evaluate if they respond to the established RQs.

With this new group of papers, the following inclusion criteria were considered: i) papers describing the application of data science in serious games; ii) papers describing data mining techniques to serious games; iii) articles describing methods for data science oriented to serious games. An article must to be related to both of the research topics "serious games" and "data mining".

The exclusion criteria are: i) duplicate articles from the same study in different sources; ii) introductory documents for special issues, books, and workshops; iii) articles that are not written in the English language; iv) articles that are only available as presentations, abstracts, v) incomplete articles without research design such as workshops, surveys or without well-defined research questions, vi) publications that have not undergone a formal review process or technical reports; and, vii) short articles with less than five pages.

3.1.4 Quality Assessment

To evaluate the found articles, a group of questions were proposed. These questions allowed the classification of their quality, by assigned points based on the answer to said questions. The questions formulated along with their proposed answers are represented in Table 1.

Table 1: Quality assessment.

#	Question	Answer and score
QA1	Does the study present topics about data science in serious games?	Agree (+1) Partially (0) Disagree (-1)
QA2	Has the study been published in a relevant journal or conference (Scimago Journal & Country Rank)?	Very relevant (+1) Relevant (0) Not relevant (-1)
QA3	Has the study been cited by other authors?	Yes, more than 5 (+1) Partially, from 1 to 5 (0) No, it has not (-1)

The quality assessment has to be applied to each article, so that its quality and scientific relevance can be identified. Also, the Fleiss' Kappa measure was calculated. It obtains the agreement among raters, assigning a coefficient evaluated through a matrix of ranges and equivalences (McHugh, 2012).

3.2 Conducting the Systematic Literature Review

All metadata of each article were extracted. Then, a matrix to organize the information was created with the research questions and sub-questions that represent the main features to be considered in this SRL. From the repository, Table two shows the number of articles that respond to each extraction criterion, the percentage in relation to the total of selected articles and one or more references. For example, the EC1 looks for the deployment location, where a console, an app, a website, or other location is considered. 52 articles answer this EC, but they can mention more than one answer, for examine the game can be deployed in an app and over the web.

In the next step, a full paper lecture of each article is performed to complete the matrix above. For achieving, a binary qualifier (1,0) was used to indicate the presence or absence of that feature. This matrix is used to analyze the contents and measure the articles' quality assessment.

3.3 Reporting the Results

This subsection presents the results of the SLR. It is divided into two phases.

3.3.1 Search Results

The articles were retrieved from the sources mentioned in 3.1.2; each article was read to evaluate if it satisfies the inclusion and exclusion criteria described in section 3.1.3. A total of 591 articles were retrieved, 57 articles were published in more than one database, so they were excluded.

The title, abstract, and keywords of the remaining 534 articles were reviewed; the number of citations and the article's publication date were also considered. Each RQ was evaluated, and if the article answered at least one criterion (EC), information was extracted and registered into the matrix; otherwise, the article was rejected. A total of 60 articles was selected for a complete reading and extraction of RQs. Figure 1 presents the entire process. Figures, tables and appendixes are stored in a repository available at https://bit.ly/3oQpQZy.

3.3.2 Assessing the Quality

For the quality of each article, three questions were evaluated per article, and the statistical measure Fleiss' Kappa was calculated.

Three different research team members read each article, applied the inclusion and exclusion criteria, read and answered the RQs. The reading for at least three members is mandatory since it is the minimum to construct the Fleiss' Kappa measure.

The Fleiss' Kappa indicator measures the level of agreement between 3 or more reviewers of the articles. To calculate it, 5 articles of the 60 were selected; a value of 0.61 was obtained. According to the table of ranges (Nichols et al., 2010), a moderate level of agreement is evidenced.

Table 3 presents the questions and the percentage obtained. Again, it is remarkable that the averages for the topic and the journal's relevance are over the mean.

4 DISCUSSION

This section focuses on presenting the main findings obtained from the extraction matrix. Aspects of data mining, their techniques, and algorithms have been considered. Appendix 1 shows the list of selected articles, and Appendix 2 presents the number of articles that answer each RQ and their percentage.

RQ1 has eight extraction criteria. In EC1, it can be seen that APP is the most common deployment location (50%), followed by the Web (28.85%), only 21.15% of serious games are implemented by consoles. EC2 presents the results for deployment platforms, where computers are the most used devices with 62,50%, while telephones and tablets show lower percentages of 21,43% and 16,07%, respectively. These scores show the need to develop serious games compatible with various deployment locations and different devices. EC3 presents the study area where Education (64,91%), a field where most serious games are developed. Health is another area that catches the attention of an influential audience (22,81%). Business and other areas represent less than 13%. Age is analyzed in EC4, where most games are aimed at adults (63.41%) and a small percentage for children (36.59%). There are no articles that show that data science techniques have been applied in serious games aimed at older adults. There are no articles that show that data science techniques have been applied in serious games aimed at older adults. Recollecting and analysing data from this age group applying data science is considered an untapped area at the moment. EC5 presents programs as the most used development tool (62.50%). 37.51% of articles present methodologies, and only one article presents a framework (1.79%). EC6 features single-player games with the highest percentage (50%), followed by multiplayer games (21.05%). If the game presents scores, it is analyzed in EC7. Most do not, with 55.32%, 44.68% shows a positive answer. Scores, ages, and other options are used to classify users in EC8. Scores represent the most common manner with 80%.

RQ2 presents different data science techniques applied to serious games. EC9 Present Sampling as the most used data preprocessing technique with 91%. Decision trees (35%) and Bayesian networks (30%) are the most used classification techniques in EC10. SVM represents 13%, KNN and ANN are the remaining 4%. Clustering techniques are analyzed in EC11. K-means has the highest percentage (81.25%), hierarchical message passing represents 12.50%, and density-based only 6.25%. Few articles include the data storage technique in EC12; 2 uses JSON; and 3, SQL. This fact of not including the data storage procedure limits the possibility of identifying the best way to apply data science.

In RQ3, EC13 identifies academia as where most serious games are developed (64.91%). 21.05% covers the Medicine area. This fact shows that serious games are a current line of research in academia. EC14 presents the evaluation of the serious game. Analysis (40.60%) and tests (31.3%) are the most developed evaluations; only 28.1% focus on implementation, but none on design.

RQ4 presents the topics related to research. The validation is analyzed in EC15. Controlled experiments are the most frequent manner of validation (57%), followed by proof of concepts (25%) and case studies (19%). The most representative area of development is the academy, with 85.45%. The industry registers 14.55% in EC16. Finally, EC17 presents the study continuity, where 55.36% are new researches, and44.64% are continuations.

The most relevant findings for this SLR are related to demographic variables of age and application area analyzed according to preprocessing, classification, and clustering.

Figure 2(a) shows different areas where data preprocessing techniques have been applied. Again, sampling is the most used technique.

For example, the author of A003 performed a preprocessing on data from students to test its effectiveness in learning in students (Wang & Huang, 2021).

Figure 2(b) shows the types of users of serious games, according to ages ranges and the different preprocessing techniques used. It can be observed that there is a more significant number of studies that used data sampling in the category of users between 18 and 64 years. However, none specifies an age range more significant than 64 years.

Some studies are addressed to a specific range of age. For example, the Storyboard Interpretation Technology prototype was designed for an educational context to support students. Its main contribution is to provide an environment to understand the deeper meaning of a problem, working with students aged 11 to 13 years (Schuldt et al., 2018). PEGASO is a serious game that promotes a healthy lifestyle for teenagers. This game provides tailored interventions to motivate them using their smartphones (Carrino et al., 2014).

The information about data classification algorithms used in different development areas is shown in Figure 2(c). The relevant information is found in the area of education. To perform the classification, the Decision Trees and Bayesian networks are mainly applied.

The objective of some of these studies is to detect the behavior of students and discover those students who have some type of problem or unusual behavior (e.g., wrong actions, low motivation, misuse, cheating, abandonment, academic failure) (Suhirman et al., 2014). Several data mining techniques, classification and grouping has been widely used to reveal this type of students, and provide them with adequate help. In addition to these classification techniques, the authors used traditional statistical techniques such as factor analysis and model fit analysis, with the purpose of examining the data, and the structure of the model. Finally, the authors developed a computational model of the cognitive process, using an Artificial Neural Network (ANN), which allowed to review the underlying mechanisms of cognition.

Figure 2(d) presents the data mining techniques applied according to the age. Bayesian network along with Decision Trees were applied more frequently.

Yahuna et. al. (2017) analyzed the behavior of the participants when using a mathematical game. This is a serious game was developed to evaluate the mathematical ability of special-needs children. This game uses the Indonesian Math curriculum, for elementary school students. The game is presented with a 4-options questionnaire. So, children perform a classification and prediction that can be used to determine the content of learning, evaluation questions, and early warning. Clustering algorithms according to the development area are shown in Figure 2(e). The educational field shows the highest score where the K-means clustering algorithm was implemented.

Benmakrelouf et at. (2015) applied the K-Means data mining methods to discuss the analysis of learning through serious games. Then, an analysis of the player's experience was provided, using data collected from the educational game. This study revealed that there are three forms of player participation: beginner, intermediate and advanced, which are allocated according to their experience.

5 THREATS TO VALIDITY

Although the SLR was performed applying the methodology proposed by Kitchehman (2010), some threats to validity were mitigated during this research process.

SLR included the most remarkable databases, but it did not eliminate the fact that a small group of studies could be excluded. To mitigate this problem, a search was performed, applying different criteria in the search string in order to obtain the most significant number of studies. The reading of each article (title, abstract, and the application of exclusion and inclusion criteria) was performed by three different members of the research team; this avoided the exclusion of relevant articles. The papers selected were those approved by 2 or 3 members.

Another problem in obtaining articles was the selection of international congresses or conferences and their relevance. To mitigate this problem, the impact of each congress was evaluated, including the periodicity, sponsors, and indexation sites.

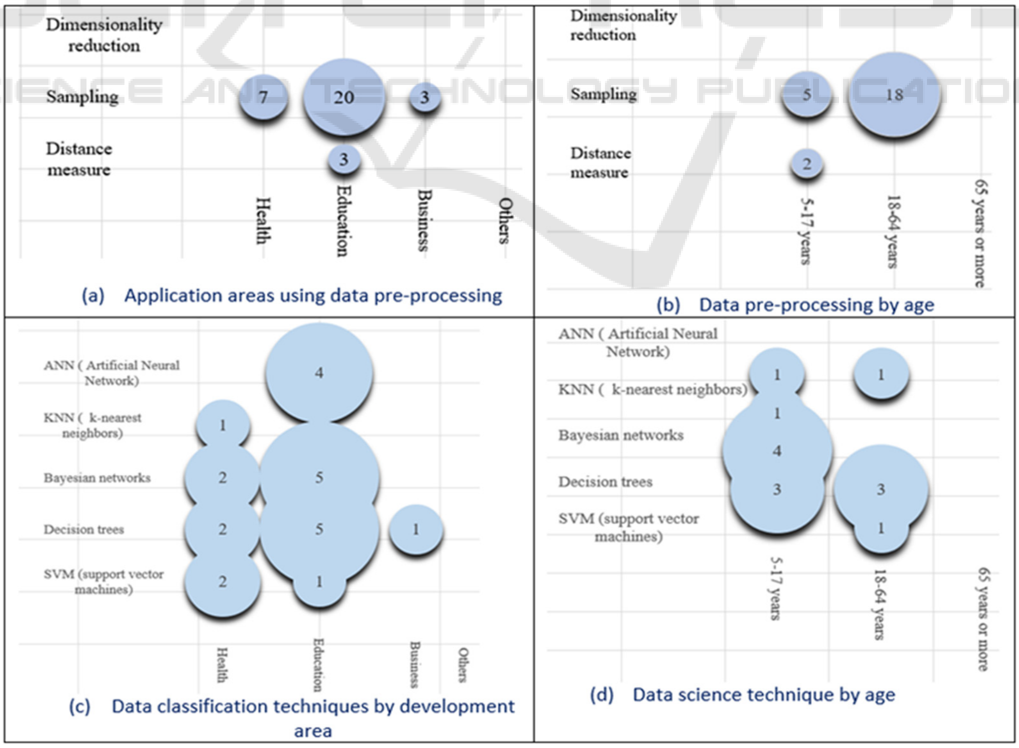

Figure 2: Bubble Plots of the Review Results.

The agreement between reviewers when assigning values to different RQs was considered. To mitigate this situation, the Fleiss' Kappa indicator was calculated, which gave a level of agreement among reviewers.

6 CONCLUSIONS

The systematic literature review was carried out using the methodology proposed by Barbara Kitchenham. This process consists of several phases that have been done successfully, obtaining answers to the different research questions. For each research question, articles that respond to these have been identified, and their quality has also been validated.

From the review, it is evident that although there are other systematic reviews in serious games, none of these focuses on data mining techniques. Instead, this review focuses on the classification of game analytics, in collaborative learning, enhancing learning but does not analyze data science techniques such as data pre-processing, classification, clustering, or data storage in a straightforward way.

Regarding the most relevant findings, the area of education is exploited to develop serious games. Many authors emphasize in the importance of improving student learning. Another area of study in serious games is health, where the lifestyle, intellectual or cognitive abilities of people are trained.

Studies show that the data sampling technique and data classification algorithms are the most widely used in data science. The Bayesian Networks and Decision Trees are the most implemented. In clustering techniques, the k-means algorithm is the most used.

This review shows that data science techniques have not been applied to analyze data collected for serious games. There is evidence of different types of serious games for different age ranges, but none of them focuses on the user's performance analysis or results, and the information that can be extracted from them. Finally, future work will focus on extracting data from serious games aimed at the elderly age group in the field of attention and cognitive memory to apply the most relevant techniques obtained in this review.

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REFERENCES

Alonso-Fernández, C., Calvo-Morata, A., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2019). Applications of data science to game learning analytics data: A systematic literature review. *Computers and Education*, *141*(April), 103612. https://doi.org/10.1016/j.compedu.2019.103612

Benmakrelouf, S., Mezghani, N., & Kara, N. (2015). Towards the identification of players' profiles using game's data analysis based on regression model and clustering. *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2015*, 1403–1410. https://doi.org/10.1145/2808797.2809429

Bente, G., & Breuer, J. (2010). Why so serious? On the Relation of Serious Games and Learning. *Eludamos - Journal for Computer Game Culture*, *4*(1), 7–24.

Carrino, S., Caon, M., Angelini, L., Mugellini, E., Abou Khaled, O., Orte, S., Vargiu, E., Coulson, N., Serrano, J. C. E., Tabozzi, S., Lafortuna, C., & Rizzo, G. (2014). PEGASO: A personalised and motivational ICT system to empower adolescents towards healthy lifestyles. *Studies in Health Technology and Informatics*, *207*, 350–359. https://doi.org/10.3233/978-1-61499-474-9-350

Chen, F., Cui, Y., & Chu, M. W. (2020). Utilizing Game Analytics to Inform and Validate Digital Game-based Assessment with Evidence-centered Game Design: A Case Study. *International Journal of Artificial Intelligence in Education*, *30*(3), 481–503. https://doi.org/10.1007/s40593-020-00202-6

Hernández, J. A. C., Duarte, M. P., & Dodero, J. M. (2017). An architecture for skill assessment in serious games based on Event Sequence Analysis. *ACM International Conference Proceeding Series*, *Part F1322*. https://doi.org/10.1145/3144826.3145400

Hou, H. T. (2015). Integrating cluster and sequential analysis to explore learners' flow and behavioral patterns in a simulation game with situated-learning context for science courses: A video-based process exploration. *Computers in Human Behavior*, *48*, 424–435. https://doi.org/10.1016/j.chb.2015.02.010

Kitchenham, B., Pretorius, R., Budgen, D., Brereton, O. P., Turner, M., Niazi, M., & Linkman, S. (2010). Systematic literature reviews in software engineering-A tertiary study. *Information and Software Technology*, *52*(8), 792–805. https://doi.org/10.1016/j.infsof.2010.03.006

Loh, C. S., Sheng, Y., & Ifenthaler, D. (n.d.). *(Advances in Game-Based Learning) Christian Sebastian Loh, Yanyan Sheng, Dirk Ifenthaler (eds.)-Serious Games Analytics_ Methodologies for Performance*

Measurement, Assessment, and Improvement-Spring.pdf.

Loh, C. S., Sheng, Y., & Ifenthaler, D. (2015). Serious games analytics: Methodologies for performance measurement, assessment, and improvement. In *Serious Games Analytics: Methodologies for Performance Measurement, Assessment, and Improvement*. https://doi.org/10.1007/978-3-319-05834-4

Massa, S. M., & Kühn, F. D. (2018). *Learning Analytics in Serious Games: a systematic review of literature; Learning Analytics in Serious Games: a systematic review of literature*.

McHugh, M. L. (2012). Lessons in biostatistics interrater reliability : the kappa statistic. *Biochemica Medica*, *22*(3), 276–282. https://hrcak.srce.hr/89395

Mendoza, F. T., Paucar, H. R., & Condori, K. V. (2019). Academic results meanings with data mining mediated by the use of serious video game matelogic. *Journal of Advanced Research in Dynamical and Control Systems*, *11*(11 Special Issue), 509–518. https://doi.org/10.5373/JARDCS/V11SP11/20193061

Nichols, T. R., Wisner, P. M., Cripe, G., & Gulabchand, L. (2010). Putting the kappa statistic to use. *Quality Assurance Journal*, *13*(3–4), 57–61. https://doi.org/10.1002/qaj.481

Petrov, E. V., Mustafina, J., Alloghani, M., Galiullin, L., & Tan, S. Y. (2019). Learning analytics and serious games: Analysis of interrelation. *Proceedings - International Conference on Developments in ESystems Engineering, DeSE*, *2018-Septe*, 153–156. https://doi.org/10.1109/DeSE.2018.00037

Ravyse, W. S., Seugnet Blignaut, A., Leendertz, V., & Woolner, A. (2017). Success factors for serious games to enhance learning: a systematic review. *Virtual Reality*, *21*(1), 31–58. https://doi.org/10.1007/s10055-016-0298-4

Ruiz-Rube, I., Dodero, J. M., Palomo-Duarte, M., Ruiz, M., & Gawn, D. (2013). Uses and applications of Software & Systems Process Engineering Meta-Model process models. A systematic mapping study. *Journal of Software: Evolution and Process*, *25*(9), 999–1025.

Schuldt, J., Sachse, S., Friedemann, S., & Breitbarth, K. (2018). Storyboard interpretation technology used for value-based STEM education in digital game-based learning contexts. *CSEDU 2018 - Proceedings of the 10th International Conference on Computer Supported Education*, *2*(Csedu 2018), 78–88. https://doi.org/10.5220/0006670700780088

Shoukry, L., Göbel, S., & Steinmetz, R. (2014). *Learning Analytics and Serious Games*. 21–26. https://doi.org/10.1145/2656719.2656729

Slimani, A., Elouaai, F., Elaachak, L., Yedri, O. B., & Bouhorma, M. (2018). Learning analytics through serious games: Data mining algorithms for performance measurement and improvement purposes. *International Journal of Emerging Technologies in Learning*, *13*(1), 46–64. https://doi.org/10.3991/ijet.v13i01.7518

Suhirman, X. X., Zain, J. M., & Herawan, T. (2014). Data mining for education decision support: A review. *International Journal of Emerging Technologies in Learning*, *9*(6), 4–19. https://doi.org/10.3991/ijet.v9i6.3950

Wang, C., & Huang, L. (2021). A Systematic Review of Serious Games for Collaborative Learning: Theoretical Framework, Game Mechanic and Efficiency Assessment. *International Journal of Emerging Technologies in Learning*, *16*(6), 88–105. https://doi.org/10.3991/ijet.v16i06.18495

Wilkinson, P. (2016). Brief history of serious games. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9970 LNCS*, 17–41. https://doi.org/10.1007/978-3-319-46152-6_2

Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., & Wesslén, A. (2012). Experimentation in software engineering. *Experimentation in Software Engineering*, *9783642290*, 1–236. https://doi.org/10.1007/978-3-642-29044-2

Yuhana, U. L., Mangowal, R. G., Rochimah, S., Yuniarno, E. M., & Purnomo, M. H. (2017, June 5). Predicting Math performance of children with special needs based on serious game. *2017 IEEE 5th International Conference on Serious Games and Applications for Health, SeGAH 2017*. https://doi.org/10.1109/SeGAH.2017.7939276

Zanasi, A., & Ruini, F. (2018). It-Induced Cognitive Biases in Intelligence Analysis: Big Data Analytics and Serious Games. *International Journal of Safety and Security Engineering*, *8*(3), 438–450. https://doi.org/10.2495/SAFE-V8-N3-438-450

Zhang, J., & Lu, J. (2014). Using Mobile Serious Games for Learning Programming. *... 2014, The Fourth International Conference on ...*, *c*, 24–29.