Seminararbeit im Studiengang Informatik - Game Engineering

Lernanalytik für Serious Games

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Kurzbeschreibung

This seminar paper gives an overview of the use of learning analytics in serious games. Mentioning information regarding learning analytics itself and the data collection, selection, analysis and visualization required for use in serious games as well as two of the most important related fields, concerns, issues and limitations of learning analytics in serious games, some promising specifications, frameworks and models for use in serious games and opportunities for improvement.

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2 INTRODUCTION

The popularity of serious games has grown over the last couple of years. Serious games find use especially in education, training and medical fields like therapy. Serious games and games in general are described by Fernández-Manjón et al. as, in most cases, "intrinsically more interactive than static learning materials such as text documents, slides or quizzes; and therefore have the potential for revealing much more information" (Fernández-Manjón et al., 2016, p. 8).

Even though, theoretically, serious games could produce a huge amount of data and by doing so, reveal possibly much more information, according to Alvarez et al. many serious games are just message broadcasters (Alvarez et al., 2011, p. 5).

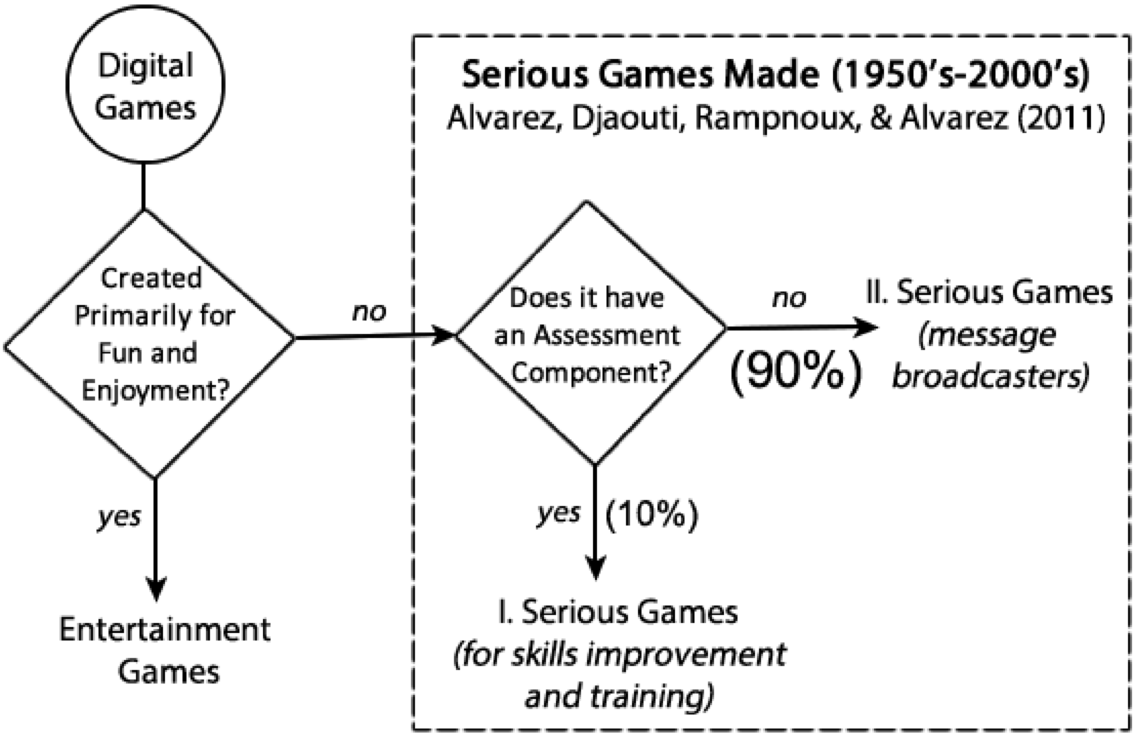

FIGURE 1: DIFFERENCE BETWEEN SERIOUS GAMES THAT USE AN ASSESSMENT COMPONENT AND SERIOUS GAMES THAT DO NOT USE ONE.

Only in a few serious games is the in-game generated data used to its full potential. Baalsrud Hauge et al. note, that although many serious games do track the progression and measure the performance of their players, high performance does not equal effective learning. (Baalsrud Hauge et al., 2014, p. 230). One of the problems that arise in serious games because of this is described by Fernández-Manjón et al.:

> A very common approach when validating a game is evaluating them exclusively in terms of their learning outcomes - known as the "if the players learn, the game is valid" approach. This is an oversimplification that neglects many of the advantages of using serious games: increased motivation and engagement, a deeper understanding of the

underlying principles being taught, and the experience gained through exploratory interactions in a safe environment. (Fernández-Manjón et al., 2016, p. 20)

According to Alonso-Fernández et al. another big issue that can occur while playing such serious games is that “learning concepts appear at different stages of the game for different players; and this learning process should be tracked in real-time through the observation of in-game interactions for optimal feedback regarding the effectiveness of the games’ learning design” (Alonso-Fernández, 2017, p. 2).

Baalsrud Hauge et al. actually go as far as to say that “many games analyze player data, but fail to analyze the learning” (Baalsrud Hauge et al., 2014, p. 231). But exactly that is a huge problem in itself, because like Chen and Michael mention, “serious games like every other tool of education must be able to show that the necessary learning has occurred” (Chen & Michael, 2005, p. 1). Bellotti et al. add to this, that “for serious games to be considered a viable educational tool, they must provide some means of testing and progress tracking and the testing must be recognizable within the context of the education or training they are attempting to impart” (Bellotti et al. 2013, p.3).

To drive the usage of serious games as educational tools forward, it is necessary to have a deeper understanding of how games affect the learning process. An improvement of this understanding can begin with better assessment. (Fernández-Manjón et al., 2016, p. 7). One of the advantages of better assessment is noted by Fernández-Manjón et al.:

> “detailed analysis of game interactions can yield detailed information about how each player interacted with the game [….] If these game-play behaviors could be distilled and presented in a meaningful way to teachers, they could be a very powerful source of information regarding student misconceptions and progress in the mastery of targeted concepts. (Fernández-Manjón et al., 2016, p. 8)

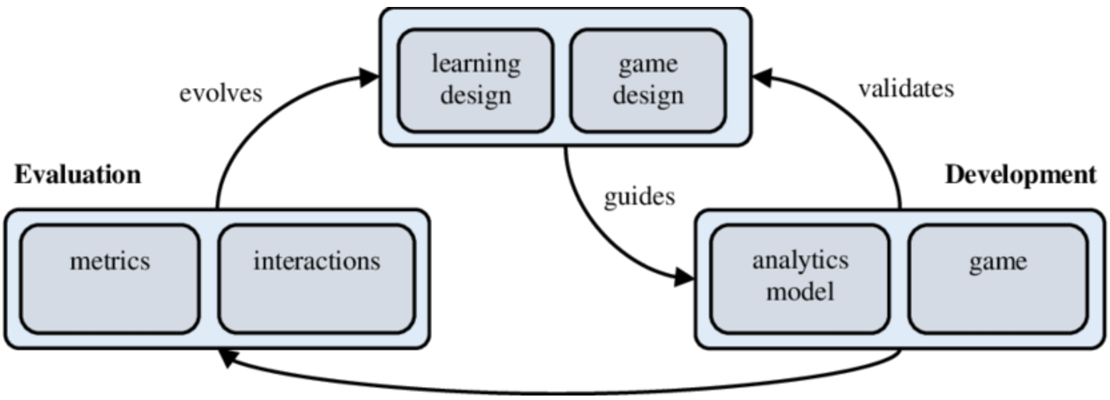

FIGURE 2: THE LIFECYCLE OF A SERIOUS GAME AS SHOWN IN “FULL LIFECYCLE ARCHITECTURE FOR SERIOUS GAMES: INTEGRATING GAME LEARNING ANALYTICS AND A GAME AUTHORING TOOL” BY ALONSO-FERNÁNDEZ ET AL.

This seminar paper will give an overview of learning analytics, one of the fields that focus on detailed analysis of interactions and learning processes. Alloghani et al. mention in their paper “Learning Analytics and Serious Games: Analysis of Interrelation” that “this relatively new approach to organization of education, despite its comparatively short period of experiencing and testing […], has already proven to bear a positive result for all the parties involved in the educational process“ (Alloghani et al., 2018, p. 153).

Section 3 will focus on Learning Analytics in general and in serious games. Section 4 will mention some learning analytics related fields, more specifically game analytics and educational data mining. In Section 5 information will be provided regarding the concerns, issues, limitations and implications for game design that come with the use of learning analytics in serious games. Section 6 will discuss some of the specifications, frameworks and models that show promise for the use in combination with serious games. Opportunities for improvement will be suggested in section 7. Section 8 will give an outlook and discuss some of the use of learning analytics in serious games and finally section 9 will summaries this seminar paper.

3 LEARNING ANALYTIC

According to Alonso-Fernández et al., the lifecycle of a serious game consists and goes from the concept to the development to validation and in the end to exploitation, during which analysis is required to generate useful feedback, including evaluation and validation of the learning process. (Alonso-Fernández et al., 2017, p. 2).

Even though serious games make more and more use of learning analytics, a clear and universally accepted definition for learning analytics does not exist. Tanya Elias describes learning analytics as an “emerging field in which sophisticated analytic tools are used to improve learning and education” (Elias, 2011, p. 2). Belahbibe et al. describe learning analytics in the following way:

> The learning analytics research trays to answer increasingly several questions about what a learner knows and whether a learner is engaged. The application fields of the learning analytics concern modeling of user knowledge, user behavior, and user experience, user profiling; modeling of key concepts in a domain and modeling a domain’s knowledge components, and trend analysis. (Belahbibe et al., 2015, p. 346)

And although that is a good description of learning analytics, according to Fernández-Manjón et al., the definition given by the 1st International Conference on Learning Analytics and Knowledge[1]: “Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs”, is one of the most accurate definitions of learning analytics. (Fernández-Manjón et al., 2016, p. 14).

Serious games without learning analytics are more or less just black boxes, that only provide a final result for the player and often do not provide any information regarding the learning process. (Alonso-Fernández et al. 2017, p. 1107). “Opening the box can provide much more information on the use of SGs and how their players interact with them” (Alonso-Fernández et al. 2017, p. 1107).

Once data has been collected Fernández-Manjón et al. explain that:

> there are two prongs in “traditional” Learning Analytics - the teacher side, and the student side. From the student side, the main aim is to let students know how they are doing in the course. [….] The other side of the equation is that of teachers/instructors, who need to track progress both to adjust the speed and contents of their courses, and to inform grading. These analyses may help instructors identify struggling students and

[1] 1st International Conference on Learning Analytics and Knowledge 2011 (LAK 2011) - https://tekri.athabascau.ca/analytics/

> maybe even offer specific remediation actions for those students. (Fernández-Manjón et al., 2016, p. 15)

Alloghani et al. note that some of the works that they reviewed suggest that there are two ways that learning analytics and serious games can interact with each other: “Learning analytics is used for improvement of Serious Games” or “Serious Games are used to improve the quality of the Learning analytics”. But in both cases, they would like to point out that “we are dealing with a quality improvement of education process” (Alloghani et al., 2018, p. 154). Adding to this, they explain that the first assumes that learning analytics can be used to improve the game process, collecting data or detecting weak points to adjust the game accordingly and the second supposes that serious games can be used to increase the quality and accuracy of learning analytics. (Alloghani et al., 2018, p. 154).

Furthermore Fernández-Manjón et al. suggest that, in the context of serious games, a combination of learning analytics and game analytics should be used:

> When creating a Serious Game, the educational goals of Learning Analytics and the tools and technologies from Game Analytics should be combined, in what could be called Game Learning Analytics (GLA). This combination can contribute to a generalization and a better use of the serious games. Having data of what is happening while the user is playing is key to relating game-play with actual learning, and to move from only theory-based approaches to more data-driven or evidence-based approaches. This in turn can help to contrast the educational approaches and eventually to better understand how the learning process happens. (Fernández-Manjón et al., 2016, p. 21)

In this seminar paper the term „learning analytics” will be used when referring to either learning analytics or game learning analytics.

The following subsections will focus on some of the most important aspects when it comes to the usage of learning analytics in combination with serious games, namely data selection and collection, the analysis of this data, the visualization as well as the implications that learning analytics has for the design of serious games, mentioning some of the requirements and benefits that come with them.

3.1 DATA COLLECTION AND SELECTION

Data collection and selection is probably one of the most important parts of learning analytics in serious games, since it delivers the basis for most analytical processes used in many models and has the potential to either make analytics deliver useful information that can be used or deliver useless information that cannot be used.

Data can mostly be generated and collected within a serious game by the software itself or externally through additional hardware such as an eye tracker. External hardware will be mentioned in more detail in section 7, since additional hardware is not used in combination with many serious games.

Alonso-Fernández et al. consider three main pillars when it comes to the management of collected data: anonymization, collection and storage. (Alonso-Fernández et al., 2019, p. 2).

- **Anonymization:** to generalize learning analytics, the gathered information should be anonymized immediately after collection, to reduce the potential risks for all parties involved (Fernández-Manjón et al., 2016, p. 38) and to comply with regulations and privacy laws (Alonso-Fernández et al., 2019, p. 2).

- **Collection:** the collection of data should be non-intrusive and transparent as far as possible. Additionally, using standard tracking models can simplify and standardize this process. (Alonso-Fernández et al., 2019, p. 2)
- **Storage:** once the data is collected it should be stored in a server that can handle large amounts of data in a secure way. (Alonso-Fernández et al., 2019, p. 2)

Alonso-Fernández et al. also give an exemplary solution to the anonymization problem, the use of pseudo-anonymization techniques, assigning random tokens to the players of a serious game and using these tokens to tie all data of a single player together, while yielding no information on the identity of said player. (Alonso-Fernández et al., 2019, p. 3).

In a perfect world every possible and obtainable piece of data should be used to analyze the learning process and behavior of a player and Alonso-Fernández et al. note that "the first step to gain insights from in-game user interactions is to ensure that all data with the potential to yield such insights is adequately collected" (Alonso-Fernández et al., 2019, p. 2), but according to Ifenthaler et al. "the idea to collect all gameplay data of play-learners indiscriminately is both inefficient and asinine" (Ifenthaler et al., 2015, p. 18) and since it is so inefficient to analyze every user interaction with the game Fernández-Manjón et al. write that "it is necessary to filter interactions that are not relevant for assessment purposes" (Fernández-Manjón et al., 2012, p. 206). The same principle of collecting data from user interactions goes for variables used in serious games, even though a game can contain a bulk of variables, in most cases, only a select few are actually significant for assessment and because of that should only generate a trace for these variables when they are final or change. (Fernández-Manjón et al., 2012, p. 205).

According to Alonso-Fernández et al., since analysis requires the collection of player individual interaction data, it is desirable to use a standard collection format to allow for interoperability and avoid data lock-in. (Alonso-Fernández et al., 2017, p. 5). One Problem with this approach is that "educational assessment is typically based on goals achieved by students in certain areas. A goal is considered fulfilled when certain conditions are met, and these conditions are heavily dependent on each specific game" (Fernández-Manjón et al., 2014, p. 6) and thus data collection should be separated into game dependent and game independent traces.

Game dependent traces would have to be defined separately for each serious game but would obviously allow for more game specific analysis of data.

Game independent traces can be defined for use in most, if not all, serious games to collect relevant information and "the more concrete the game design is, the better these traces can be defined" (Fernández-Manjón et al., 2012, p. 204). Fernández-Manjón et al. define such a set of general traces for use in serious games in their paper "Tracing a Little for Big Improvements: Application of Learning Analytics and Videogames for Student Assessment". They suggest the following traces:

- **Start, end and quit game:** the generated traces should include who generated them, when they were generated as well as contain a session identifier. The start game trace should be generated whenever the game is started. The end game trace should be generated whenever a player finishes the game. The quit game trace should be generated whenever the game is quit early without finishing it and should contain the game state at the time of quitting. It can also be periodically logged instead of when quitting.
- **Phase change:** according to them every game phase "can be associated with a secondary or mid-term goal in the game. A typical game structure is to consider the game as fulfilled or completed after all the secondary goals are fulfilled" (Fernández-

Manjón et al., 2012, p. 205). These traced should thus be logged whenever a phase starts and ends.

- **Significant variables:** traces for important variables contained within the game, like for example player health. These traces should be generated either when a variable is final or has changed.
- **User interactions:** the previous traces where in-game based, containing data on game internal information. In comparison this kind of trace contains information on how the user interacts with the game, containing low level events like mouse clicks and key presses.

(Fernández-Manjón et al., 2012, p. 205)

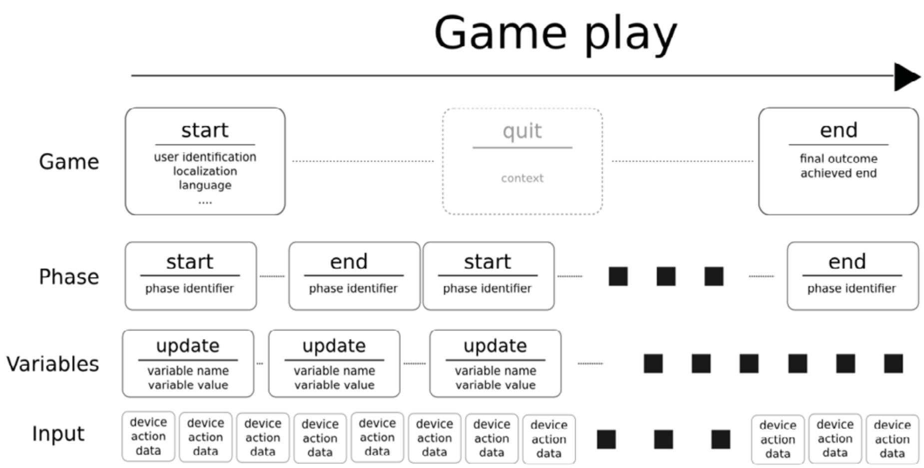

FIGURE 3: THE GAME INDEPENDENT TRACES AS DEFINED BY FERNÁNDEZ-MANJÓN, B. ET AL. IN THEIR PAPER "APPLICATION OF LEARNING ANALYTICS IN EDUCATIONAL VIDEOGAMES".

"In summary, tracing simple data is not enough by itself, and tracing advanced data is game-dependent and therefore more costly" (Fernández-Manjón et al., 2014, p. 6).

The collected data can then be sent to a server through the use of specification like the Experience API for analysis.

3.2 ANALYSIS

As stated by Alonso-Fernández et al., "the analytics model must provide information on the metrics and KPIs that will be used to prove the effectiveness of the learning design" (Alonso-Fernández et al., 2017, p. 6). They distinguish two types of analysis:

- **Game independent analysis:** analysis that is suitable for any kind of serious game that connects to the analytics server
- **Game dependent analysis:** analysis that is developed ad-hoc for each game and allows for individualization

(Alonso-Fernández et al., 2017, p. 6)

Furthermore Alonso-Fernández et al. (2019) explain that the collected data can either be analyzed in real-time (p. 4) or at a later point in time in the form of offline analysis (p. 7). Real-time analysis and feedback can be used to benefit stakeholders and for example allow a teacher to monitor students and perform timely interventions if necessary. (Alonso-Fernández et al., 2019, p. 4). And should the game implement adaptive mechanics, it can adapt itself to fit the player's needs and actions. (Alonso-Fernández et al., 2017, p. 1108).

If the data is not immediately used for displaying real-time information, it can be used, together with information from other gameplay sessions, to yield additional insights. (Alonso-Fernández et al., 2019, p. 7). And "while real-time analysis addresses users' behavior, off-line analysis can reveal patterns in how the student interacts with the game throughout the experience" (Fernández-Manjón et al., 2016, p. 25). Alonso-Fernández et al. also explain that, via the use of data mining processes, patterns of use can be extracted to improve future game deployments and administrations can make use of this aggregated data to assess if the usage of serious games is beneficial for a certain use case. (Alonso-Fernández et al., 2019, p. 7).

Although real-time and offline analysis are two different approaches, they both have the need for potentially very similar data (Baalsrud Hauge et al, 2014, p. 231) and either of them can be used to provide player with valuable feedback regarding their play sessions and allow for evaluation based on their performance (Alonso-Fernández et al., 2017, p. 1107).

Regardless of the approach taken, the data should be analyzed independently from the game (e.g. in a separate server) and should combine traces to obtain new information as well as use game specific information to infer knowledge automatically. (Fernández-Manjón et al., 2012, p. 206).

Fernández-Manjón et al. suggest a rule-based system on top of any interaction logging system, in which inputs are assessment rules defined by teachers and game-specific information. (Fernández-Manjón et al., 2012, p. 206). "The system uses the teacher-defined rules to analyze the interaction logs and infer conclusions which are reported on high-level terms" (Fernández-Manjón et al., 2012, p. 207). To avoid an enormous increase in system complexity, rules must be based on quantifiable parameter. (Fernández-Manjón et al., 2012, p. 208).

A basic set of starting points for analysis of data is suggested by Fernández-Manjón et al., in the form of the time between two points in the game, values of in-game variables and the presence of traces, all compared to values set in assessment rules by an instructor .(Fernández-Manjón et al., 2014, p. 6).

And according to Baalsrud Hauge et al. it can additionally be beneficial incorporate a semantic layer, "which translates sub-symbolic actions such as keystrokes and mouse clicks during game play into meaningful clues, related to the educational game design, game narrative, game context and the tasks carried out" (Baalsrud Hauge et al, 2014, p. 231).

3.3 VISUALIZATION

Visualization is also an important part for learning analytics in serious games. But although analysis can provide vast amounts of knowledge on students and the game, without good presentation, the interpretation of the analyzed data is difficult. (Alonso-Fernández et al., 2017, p. 3). And according to Alonso-Fernández et al.:

> To facilitate the understanding of the analysis results for a range of stakeholders [...], it is important to provide each with informative dashboards to display results. The need for easy to understand and informative visualizations is especially important in the case of teachers,

> which can greatly benefit from real-time information to monitor a class while students are playing a game, and to provide targeted feedback to students that get stuck. (Alonso-Fernández et al., 2017, p. 7)

Visualization provides teachers with “an easy way to explore the information gathered from their students’ interactions” (Alonso-Fernández et al., 2019, p. 5), can present “aggregations of individual visualizations, each providing insight into specific aspects, such as progress, errors, or choices taken” (Alonso-Fernández et al., 2019, p. 5) and “display actionable feedback to locate students that get stuck, or suggest additional work that may interest advanced students” (Alonso-Fernández et al., 2019, p. 5).

For Students visualization can “provide information on performance and in-game outcomes, allowing them to easily assess their strengths and weaknesses” (Alonso-Fernández et al., 2019, p. 7).

Visualization of aggregated data in offline analysis can yield additional insights on the behavior of players and on the learning process itself. (Alonso-Fernández et al., 2019, p. 7).

The visualization should be adjusted depending on the needs of the different stakeholders. (Alonso-Fernández et al., 2017, p. 1109). Adjustments can greatly depend on “the game, delivery environment, and the metrics and KPIs that are most relevant to each stakeholder” (Alonso-Fernández et al., 2019, p. 5). Especially advanced users must be able to tailor the visualization through dashboards to game-specific needs. (Alonso-Fernández et al., 2017, p. 1109). And although achievement of the most informative results requires ad-hoc visualization, a set of default dashboards should be provided. (Alonso-Fernández et al., 2017, p. 3).

3.4 IMPLICATIONS FOR GAME DESIGN

The use of learning analytics in combination with serious games comes with a lot of implications for the design of these serious games. These implications come in two variants.

On one side there are the implications that learning analytics have on how the game should be designed, acting more or less as requirements to maximize the benefits that can be gained through learning analytics.

On the other side are the implications it has on how the game design can benefit and use the knowledge resulting from analysis.

The game platform that the serious games use, must allow for the generation and the collection of traces containing information about the game and its users. (Fernández-Manjón et al., 2012, p. 208). Alonso-Fernández et al. claim that “the best analytics models are those that are designed together with the game itself, and are both influenced by the game’s design and, where necessary, result in changes to the design that make the resulting game easier to analyze” (Alonso-Fernández et al., 2017, p. 4). This integration in the game itself, greatly reduces the time that a serious game developer must invest in order to benefit from learning analytics, increasing the likelihood that the design can be improved throughout the game’s lifecycle. (Alonso-Fernández et al., 2017, p. 6).

Although the implementation of learning analytics from the get-go might seem challenging and maybe even aversive, the benefits of using learning analytics outweigh the risks and challenges by far. Alonso-Fernández et al. consider “that information from in-game user’s interactions can benefit all phases of a serious game’s lifecycle, including game design, development, piloting, acceptance, evaluation and maintenance” (Alonso-Fernández et al., 2019, p. 1).

Furthermore, the collected information can provide priceless insight into the reliability of the game (Fernández-Manjón et al., 2016, p. 26) as well as “trace the evolution of each player’s knowledge at every part of the game” (Alonso-Fernández et al., 2017, p. 1107). A couple examples would be:

- **Heat maps analysis:** through the analysis of heat maps, points in the game could be identified where the solution is unintuitive and the player fails to interact with the right element. (Fernández-Manjón et al., 2012, p. 206).
- **Difficulty adjustment:** aggregated player interaction data can be analyzed so that level design and the difficulty of the level or game can be evaluated (Alonso-Fernández et al., 2017, p. 1107). The difficulty of the game can be raised or lowered accordingly to improve the player experience and keep them interested.
- **Bug fixes:** the collected data can be used to find unreachable areas and unintended behavior within the game and by doing so improve future versions of the game. (Alonso-Fernández et al., 2019, p. 8).

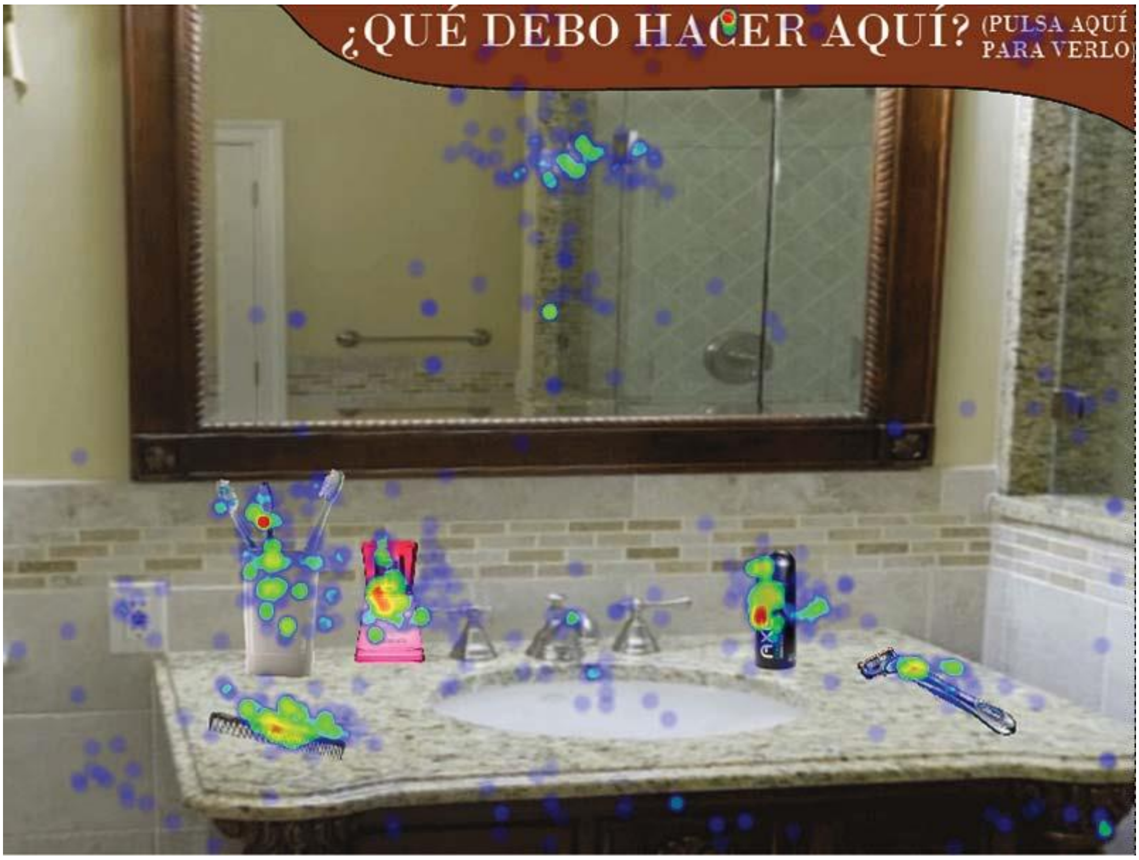

FIGURE 4: A HEATMAP FROM THE GAME “THE BIG PARTY” AS SHOWN IN “APPLICATION OF LEARNING ANALYTICS IN EDUCATIONAL VIDEOGAMES” BY FERNÁNDEZ-MANJÓN ET AL. IT SHOWS A SCENE AND THE CLICKS PERFORMED BY PLAYERS IN THE FORM OF A HEAT MAP.

4 RELATED FIELDS

Learning analytics has a close connection with a row of different fields, for example business intelligence, web analytics, academic analytics, educational data mining and action analytics. (Elias, 2011, p. 2). In combination with serious games and potentially huge amounts of data, two fields especially gain significance. On one hand there is game analytics and on the other educational data mining. These two fields will be discussed and compared to learning analytics in more detail in the following subsections.

4.1 GAME ANALYTICS

Game analytics are being used in pretty much every game there is. The metrics of game analytics provide developers with important data, which can be used to, amongst other things, improve game design which also leads to improvements to the overall gameplay experience, and to enable developers to estimate more easily what kind of content and changes their players wish for and by doing so, increase player retention, attract new players and increase revenue. (Ifenthaler et al., 2015, p. 22).

Serious games can also benefit from game analytic techniques. (Fernández-Manjón et al., 2017, p. 2). According to Fernández-Manjón et al., "all these Game Analytics techniques have evolved separately from Learning Analytics, with a very different vocabulary and typically with a different agenda" (Fernández-Manjón et al., 2016, p. 20). Alonso-Fernández et al. define one of the key differences between learning analytics und game analytics:

> The key difference between GA and LA […] is GA's exclusive focus on the game itself. In traditional GA, analytics are only intended for game-developers or, at the very most, to obtain financial information […]. Furthermore, traditional GA has no concept of tracking learning, and cannot accommodate teachers that want to explore what players have learnt and, possibly, share results with other teachers for comparison or research purposes. (Alonso-Fernández et al., 2017, p. 1108)

One of the resulting problems is that many game analytics techniques often only find usage in game-specific applications and therefore lack the specialized requirements of an educational context (Fernández-Manjón et al., 2014, p. 2).

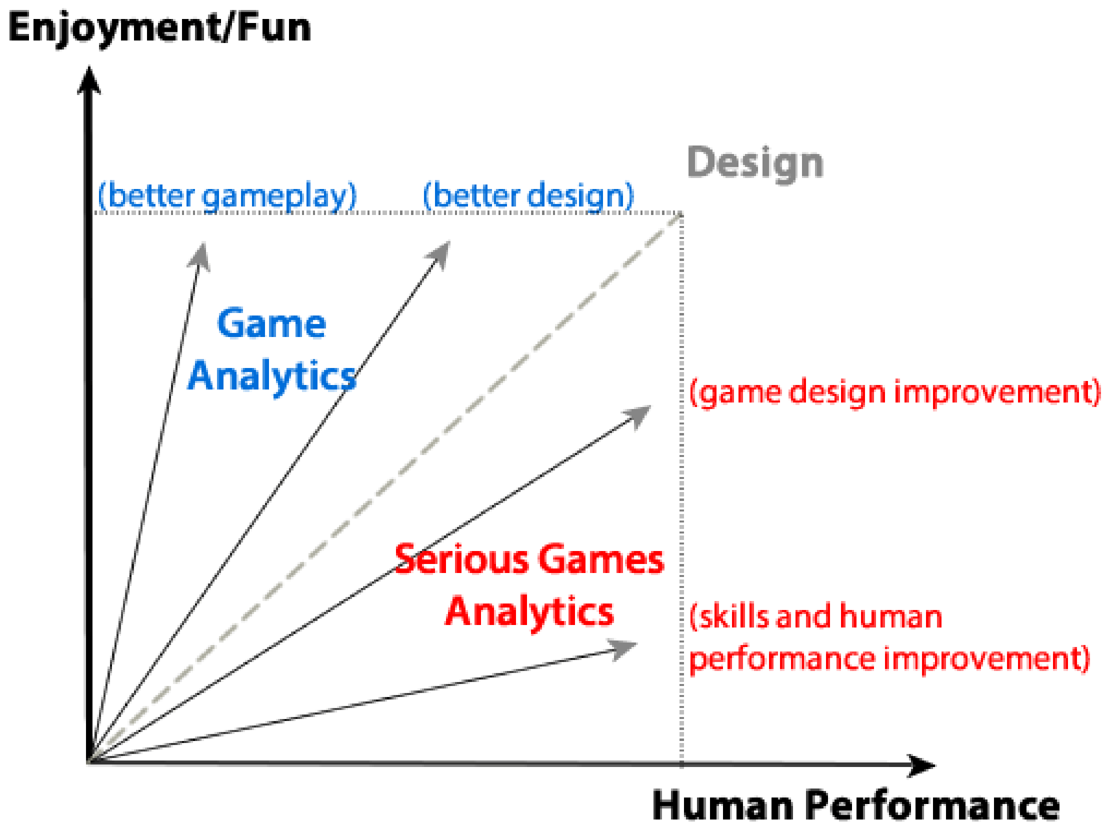

FIGURE 5: DIAGRAM SHOWING THE DIFFERENT EMPHASES OF GAME ANALYTICS AND ANALYTICS USED IN SERIOUS GAMES.

Although learning analytics and game analytics evolved separately and have mostly different goals, "both disciplines look for games with a better user experience and offer very exciting opportunities when combined in an educational game" (Fernández-Manjón et al., 2016, p. 20).

4.2 EDUCATIONAL DATA MINING

Baker and Inventado write that educational data mining can be seen in two ways, "either as a research community or as an area of scientific inquiry" and following that describe that "as a research community, EDM can be seen as a sister community to learning analytics" and "as an area of scientific inquiry, EDM is concerned with the analysis of large-scale educational data, with a focus on automated methods" (Baker & Inventado, 2014, p. 61).

They compare educational data mining and learning analytics and write that "there is considerable thematic overlap between EDM and learning analytics. In particular, both communities share a common interest in data-intensive approaches to education research, and share the goal of enhancing educational practice" (Baker & Inventado, 2014, p. 61). Furthermore, according to Baker and Inventado (2014), they also have many interesting differences (p. 62). One of those differences is the different focus. They write that learning analytics has a bigger focus on human interpretation of data and visualization (p. 70), while educational data mining is more focused on automated methods (p. 70).

In comparison to that, Bienkowski et al. describe one of the main differences as followed:

> Learning analytics draws on a broader array of academic disciplines than educational data mining, incorporating concepts and techniques from information science and sociology, in addition to computer science, statistics, psychology, and the learning sciences. Unlike educational data mining, learning analytics generally does not emphasize reducing learning into components but instead seeks to understand entire systems and to support human decision making. (Bienkowski et al., 2014, p. 13)

Learning analytics and educational data mining have a number of methods in common (Baker & Inventado, 2014, p. 70) and learning analytics also uses methods from educational data mining to analyze large datasets. (Avella et al., 2016, p. 18).

Baker and Inventado mention the four major classes of methods used in educational data mining in their publication “Educational Data Mining and Learning Analytics”. Those four classes consist of the following:

- **Prediction methods:** prediction methods try to “develop a model which can infer a single aspect of the data from some combination of other aspects of the data” (Baker & Inventado, 2014, p. 63) and are most commonly used to “predict what a value will be in contexts where it is not desirable to directly obtain a label for that construct” (Baker & Inventado, 2014, p. 63). Baker and Inventado also mention that prediction methods in addition can “be used to study which specific constructs play an important role in predicting another construct” (Baker & Inventado, 2014, p. 63).
- **Relationship mining:** relationship mining tries to find the relation of variables of a large number of variables in a specific dataset. (Baker & Inventado, 2014, p. 65). By Baker and Inventado suggested forms this could take are the attempt to find associated variables of a single specific variable or the attempt to find the strongest relationships between two variables. (Baker & Inventado, 2014, p. 65).
- **Structure discovery**: structure discovery tries to find a structure within data without any ground truth or knowing what should be found. (Baker & Inventado, 2014, p. 67). Less attention is usually given to validation than in prediction methods, since no ground truth exists. (Baker & Inventado, 2014, p. 67). Probably one of the most interesting methods of structure discovery for learning analytics is clustering. Clustering has the goal of “finding data points that naturally group together and can be used to split a full dataset into categories” (Bienkowski et al., 2010, p. 10) and are most useful when it is unknown in advance which categories are the most common in the dataset. (Baker & Inventado, 2014, p. 67). The grain size of a cluster can vary depending on what should be clustered together. (Baker & Inventado, 2014, p. 67). And according to Baker and Inventado, “clustering algorithms typically split into two categories: hierarchical approaches […], and non-hierarchical approaches […]” (Baker & Inventado, 2014, p. 67) with the key difference being that hierarchical approaches assume that clusters group together and non-hierarchical approaches assume that clusters are separate from other cluster. (Baker & Inventado, 2014, p. 68).
- **Discovery with models:** discovery with models tries to create a model of a phenomenon through the use of prediction, clustering and sometimes knowledge engineering and this model is then used in another analysis or model. (Baker & Inventado, 2014, p. 68).

These classes of methods in educational data mining can be used in learning analytics in serious games to help get a better understanding of information and can lead to an overall better analysis of gathered data.

5 CONCERNS, ISSUES AND LIMITATIONS

With the usage of learning analytics in serious games comes a variety of concerns, issues (partially ethical) and limitations. This section will mention a select few of these problems to show that learning analytics in serious games cannot just be implemented without issues and requires a lot of improvements in certain areas.

One of the probably biggest ethical issues is the collection, storage and usage of the personal information of players that serious games can gather through learning analytics. Like Drachsler and Greller mention, “personal data enjoys strong legal protection, differing by national laws and sometimes competing with other legal frameworks such as the Freedom of Information Act in the United Kingdom” (Drachsler & Greller, 2012, p. 50), so whenever a serious game developer would try to make use of learning analytics, they need to take great care and pay a lot of attention to detail, to make sure that their use of personal data does comply with local and, depending on the application, international laws and regulations. (Fernández-Manjón, 2016, p. 38).

Furthermore, when gathering personal information, the possibility that the players show some form of resistance and aversion is quite high, since many people to not like to share personal information, even if it is compliant with law and regulations. (Drachsler & Greller, 2012, p. 50). To reduce these concerns the use of this data may require that personal information is anonymized. (Drachsler & Greller, 2012, p. 50).

Besides, Drachsler and Greller note that ethical concerns do not stop at the collection of personal data:

> The realisation that we may encounter conflicts in values and interests in and through the analysis of people’s behaviour needs to guide the post-analytic decision making process and the conclusions drawn from the approach. It is important to remind stakeholders of LA processes that data can be interpreted in many ways and lead to very different consequent actions. To give a drastic example, imagine being confronted with the insight that children from an immigrant background show reading difficulties, backed by supportive data analysis. (Drachsler & Greller, 2012, p. 51)

It is obvious that Instructors that want to make use of serious games would have to be trained to interpret the analyzed and visualized data as well as to configure the analysis and visualization tools to fit their needs.

In addition, it must be made sure that the gained and analyzed data is not misinterpreted as well as that the methods used for analysis actually analyzed the collected data in the right way and delivered valid results.

Another issue is the storage of such large amounts of data. Depending on which area of deployment such serious games find usage in, it can still cause financial issues, since “despite the falling cost of data storage, keeping huge amounts of data around can still be a pricey affair” (Ifenthaler et al., 2015, p. 18). Especially for institutions that rely on funding, it can be just not worth to invest in serious games that make use of learning analytics to improve learning.

A third problem arises regarding the implementation and lack of standards of learning analytics into serious games. When implementing learning analytics, the developer must pay more attention, since “it also has to track, collect, store, analyze and visualize the in-game and user data. It may cause additional hardware requirements and, consequently, can lead to additional financial expenses” (Alloghani et al., 2018, p. 155). Fernández et al. suggest that the ad-hoc implementation of learning analytics in many serious games is another reason for the scarce usage of learning analytics in serious games and because of that, should adopt standards to increase interoperability and reduce development cost. (Alonso-Fernández et al., 2017, p. 1107).

6 SPECIFICATIONS, FRAMEWORKS AND MODELS

Traditional assessment of serious games is usually done by asking questions or conducting written tests after the player is done with the serious game. (Fernández-Manjón et al., 2014, p. 3). The issue with this is that many serious games make use of this black box model and only report final results, which deliver by far less information than is possible with tracking player interactions throughout the game. (Alonso-Fernández et al., 2017, p. 1).

One of the main problems of the use of learning analytics in serious games is that there is a lack of adapted and standardized models (Alonso-Fernández et al., 2017, p. 1107) and that is why many researchers and authors in the field of learning analytics and serious games mention promising specifications and propose their own models to combat some of the issues that come with game-specific, ad-hoc designed implementation of learning analytics in serious games, like reduced scalability, increased development cost and lower tracking interoperability between platforms and serious games.

The following subsections will list some of the most promising specifications, frameworks and models that can be used to combine serious games and learning analytics. Mentioning Caliper Analytics and the Experience API for use of transmitting data from the game to analysis component, whereas the latter is probably more useful for use in serious games, the GLEANER framework, the requirements for the basic implementation of a game learning analytics system, the RAGE Analytics environment and Meta-LAMs, an extension of a simple Learning Analytics Model for use in more complex serious games that contain multiple levels or sub-games.

6.1 CALIPER ANALYTICS

The Caliper Analytics framework is developed by the IMS Global Learning Consortium[2]. (Fernández-Manjón et al., 2016, p. 6). According to Fernández-Manjón et al. the main goal of Caliper Analytics is to "establish a way to capture and obtain measures from a set of learning activities" (Fernández-Manjón et al., 2016, p. 6).

Fernández-Manjón et al. describe that it associates learning activities with one or multiple metric profiles. Each metric profile defines an information model which shapes the different types of events that a learning activity emits. (Fernández-Manjón et al., 2016, p. 6). Metric profiles are designed to either track raw user activities or track outcomes of user learning. (Fernández-Manjón et al., 2016, p. 6). Additionally, the framework also provides a semantic for later analysis. (Fernández-Manjón et al., 2016, p. 6).

[2] IMS Global Learning Consortium, Caliper Analytics - http://www.imsglobal.org/activity/caliper

According to the IMS Global website[3] the Sensor API used in Caliper analytics is used to "define basic learning events and to standardize and simplify the gathering of learning metrics across learning environments".

The event structure is based on activity streams and contains, an actor, action and object among others. (Fernández-Manjón et al., 2016, p. 7). Regarding the use of Caliper Analytics in learning analytics in serious games, Fernández-Manjón et al. write that the extensions attribute could be used to extent most metric profiles, but for use in their game learning analytics system it would require a whole new vocabulary and a whole new metric profile would be needed to represent serious games as learning activities, which the first version of Caliper Analytics that they used does not provide. (Fernández-Manjón et al., 2016, p. 7).

6.2 EXPERIENCE API (XAPI)

The Experience API, also called Tin Can API or xAPI for short, is a specification created by the Advanced Distributed Learning Initiative[4] in collaboration with an open community and developed since back in 2010. According to Fernández-Manjón et al. "the specification's objective is to define a data and communication model to track user activities within learning environments" (Fernández-Manjón et al., 2017, p. 7) and "it is considered the 'new generation of SCORM'" (del Blanco et al., 2013, p. 1258). Del Blanco et al. write that "the Experience API is focused on defining an interoperable data model for storing data about students' learning experience and an API for sharing these data among systems. It also addresses some of SCORM's shortcomings regarding data access" (del Blanco et al., 2013, p. 1258).

Fernández-Manjón et al. write that the format derives form activity streams and events tracked in a learning activity are defined as a statement. They further explain statement consists of the following three main attributes:

- Actor
- Verb
- Object

Statements can contain additional attributes which can hold more information about the learning activity events such as:

- Result
- Context
- Authority

(Fernández-Manjón et al., 2017, p. 7)

The attributes are explained more deeply by del Blanco et al.:

- Actor: usually the learner
- Verb: describes the action performed by the student and includes a URL with a definition of this verb

[3] IMS Global Learning Consortium, Caliper background - http://www.imsglobal.org/activity/caliper#caliperbackground

[4] Advanced Distributed Learning Initiative - https://adlnet.gov

- **Object:** represents “who” or “what” experienced the action and also contains a URL with their definition
- **Result:** contains the outcome of the statement
- **Context:** contains contexts like relationship of the activity with other activities

(del Blanco et al., 2013, p. 1258).

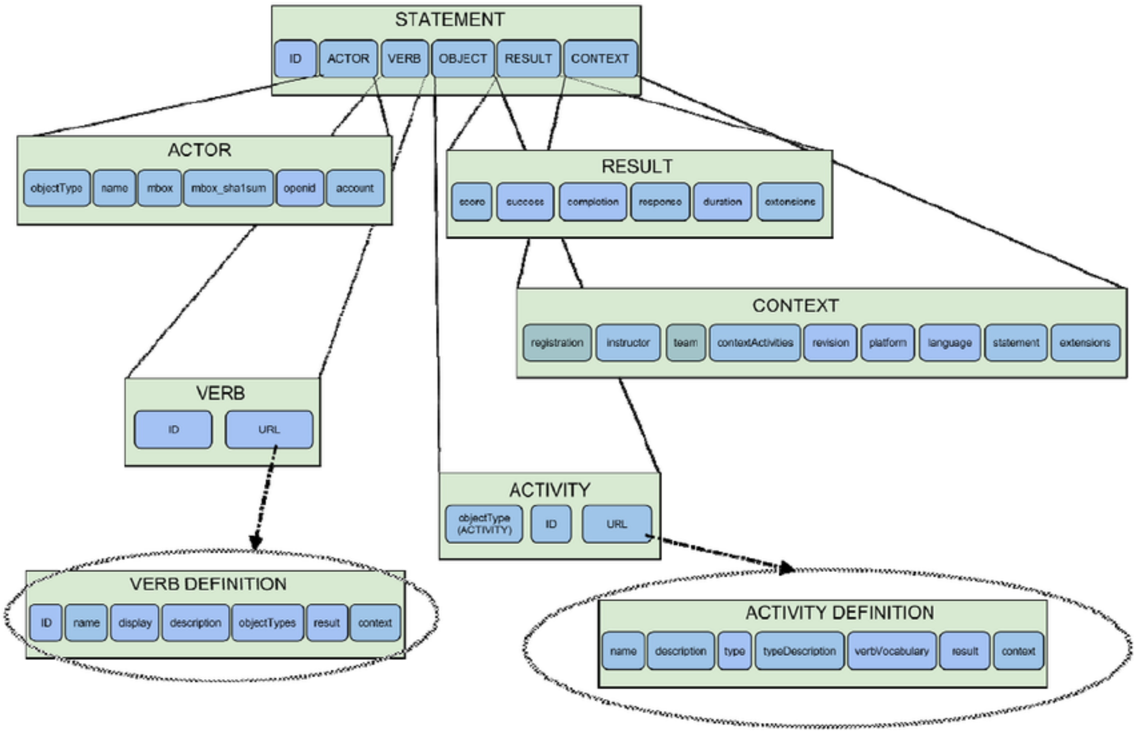

FIGURE 6: AN OVERVIEW OF THE EXPERIENCE API DATA MODEL, SHOWING THE STATEMENT AND ITS POSSIBLE COMPONENT.

A database known as a Learning Record Store is the central element of the Experience API (del Blanco et al., 2013, p. 1258) and after a statement is created it is sent to this Learning Record Store and stored there for later analysis in sequential order. (Fernández-Manjón et al., 2017, p. 7).

One advantage of the Experience API specification is that it does not set any restrictions on the vocabulary used in statements and allows the creation of new vocabularies in the form of xAPI profiles and because of that, can be used by developers and users to create vocabularies tailored to individual and use case specific applications. (Fernández-Manjón et al., 2017, p. 8).

```
{
  "actor": {
    "name": "John Doe",
    "mbox": "mailto:johndoe@example.com"
  },
  "verb": {
    "id": "http://adlnet.gov/expapi/verbs/completed",
    "display": { "en-US": "completed" }
  },
  "object": {
    "id": "http://example.com/activities/programming-course",
    "definition": {
      "name": { "en-US": "Programing course" }
    }
  }
}
```


FIGURE 7: AN EXEMPLARY EXPERIENCE API STATEMENT. IT SHOWS THAT A USER NAMED JOHN DOE COMPLETED A PROGRAMING COURSE.

The e-UCM e-learning group[5] in collaboration with Advanced Distributed Learning have created a xAPI profile for use specifically in serious games, the Experience API for Serious Games Profile or short xAPI-SG.

According to Fernández-Manjón et al, the vocabulary is designed to conceptualize the most used concepts that can be found in serious games and the goal of the vocabulary and profile is the establishment of a basis for the application of learning analytics standards in serious games. (Fernández-Manjón et al., 2017, p. 9).

If the vocabulary of the serious games profile is still not enough for developers of certain serious games, it can always be extended further to fit even the most specific needs of a serious game.

[5] eUCM – eLearning research - https://www.e-ucm.es/

```
{
  "actor": {
    "name": "John Doe",
    "mbox": "mailto:johndoe@example.com"
  },
  "verb": {
    "id": "https://w3id.org/xapi/adb/verbs/selected",
    "display": { "en-US": "selected" }
  },
  "object": {
    "id": "http://rage.e-ucm.com/activities/Countrix/questions/Capital_of_Spain",
    "definition": {
      "type:" "http://adlnet.gov/expapi/activities/question"
    }
  },
  "result": {
    "response": "Lisbon",
    "success": false,
    "extensions": {
      "https://w3id.org/xapi/seriousgames/extensions/health": 0.34
    }
  }
}
```


Figure 8: An exemplary Statement of the Serious Games profile of the Experience API. It shows that a player named John Doe selected the wrong answer to a question about the Capital of Spain, including the health of the player.

6.3 GLEANER

The **G**ames and **Le**arning **A**nalytics for **E**ducational **R**esearch (GLEANER) framework was developed by Baalsrud Hauge et al., as a part of a joint research activities in GALA, the Games and Learning Alliance. (Baalsrud Hauge et al., 2014, p. 231). In their paper “Implications of learning analytics for serious game design” they describe that it consists of a Learning Analytics Model and a Learning Analytics System. The Learning Analytics Model defines the sequence and information that is required for a number of steps, whereas the Learning Analytics System implements the required processing functions, collects all game generated traces and can be remotely located. Gathered information is pushed by the game to the Learning Analytics System through the use of a specific API. Both, the Learning Analytics Model and System consist of five interlinked components:

1. Data selection/capturing
2. Data aggregation
3. Data reporting
4. Data evaluation
5. Game adaptation

(Baalsrud Hauge et al., 2014, p. 231)

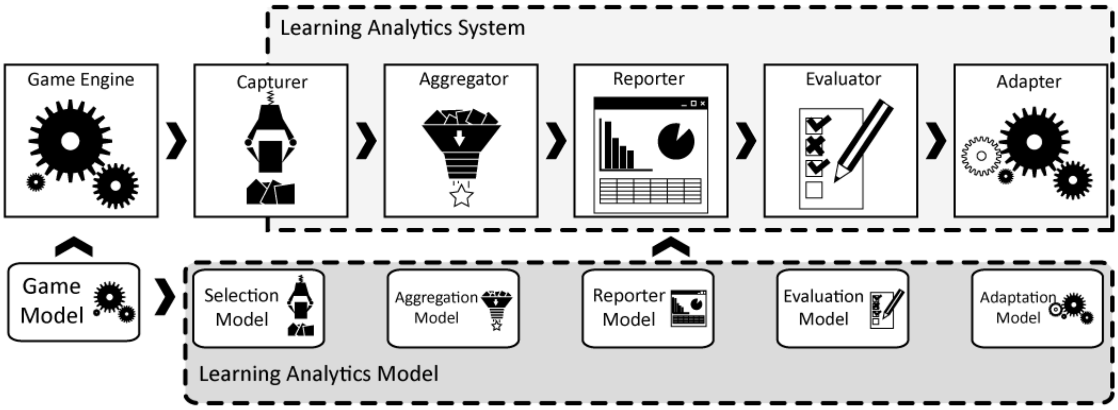

FIGURE 9: THE MAIN COMPONENTS OF THE GLEANER FRAMEWORK.

In "Learning Analytics Architecture to Scaffold Learning Experience through Technology-based Methods" Arnab et al. describe the separate steps in a bit more detail:

In the first step interactions are being reported to the capturer by the game engine and data is filtered according to the selection model.

In the second step the data is filtered by the aggregator and possibly aggregated and transformed from a set of low-level traces to higher-level traces according to the aggregation model.

In the third step the reporter visualizes data and statistics in a human-friendly way in line with the instructions in the reporter model.

In the fourth step the evaluator module assesses the learning experience, comparing traces against learning goals described in the evaluation model.

In the fifth step reported information is used by the adapter to adjust game states, depending on the adaptation model.

(Arnab et al., 2015, p. 33)

To obtain maximal benefits form learning analytics, the implementation of GLEANER should already be considered during the game design to link educational goals and in-game data to support their collection. (Baalsrud Hauge et al., 2014, p. 231).

Multiple case studies have been conducted involving the GLEANER framework and briefly outline its possibilities. (Arnab et al., 2015, p. 39). One of these studies used a serious game with the name Lost in Space <XML>. According to Fernández-Manjón et al. Lost in Space <XML> is "a puzzle game designed to learn basic XML and DTD concepts" (Fernández-Manjón et al., 2014, p. 10). The game has different phases that get incrementally harder and the goal is to fly a spaceship from a start location to a wormhole. (Fernández-Manjón et al., 2014, p. 10). To guide the spaceship the player has to type commands in the form of XML code. (Fernández-Manjón et al., 2014, p. 10). Their intention with this game was for students to have to "apply frequently the knowledge recently acquired as they played by writing actual XML documents that were the main source for assessment data" (Fernández-Manjón et al., 2014, p. 11).

They set three assessment conditions:

- **Score goal:** the game reported variation in the score variable and it was considered successful once the value it at least 1000.
- **Valid XML documents:** a variable containing the percentage of correct XML code was reported by the game and considered successful if it was higher than 75%.
- **Completion time:** the time it took for the player to finish the game. It was considered successful if it stayed beneath 30 minutes.

(Fernández-Manjón et al., 2014, p. 11)

They mention that in total 37 students of a web programming course tested the game and 94% of students completed the game successfully. (Fernández-Manjón et al., 2014, p. 11). According to them the results "successfully allowed the instructors to get basic feedback about how well each student had performed during the play session" (Fernández-Manjón et al., 2014, p. 12). It allowed him to find individual differences and common points of difficulty. (Arnab et al., 2015, p. 39).

6.4 GAME LEARNING ANALYTICS SYSTEM

As mentioned in section 3, Fernández-Manjón et al. consider that in serious games a combination of the tools used in learning analytics and technologies used in game analytics should be used to analyze the effectiveness of learning achieved within them. (Fernández-Manjón et al., 2016, p. 21).

This section will give an overview of the aspects that a basic implementation of such a game learning analytics system would need and benefit from, according to the paper "Game Learning Analytics: Learning Analytics for Serious Games", written by Fernández-Manjón et al., and after that describe the two steps that Alonso-Fernández et al. consider to help make game learning analytics more systematic.

The architecture of the game learning analytics system is based on the GLEANER framework mentioned in the previous section.

A basic implementation must store detailed information on player interactions and game state changes to analyze further (Fernández-Manjón et al., 2016, p. 21) and would require the following artifacts:

- **Instrumentation:** a game-side component that is responsible for storage of player interaction data and sending this data to a server for analysis
- **Collection and Storage:** a server-side component that classifies and stores all received information
- **Real-time analytics:** it should be possible to analyze important information in near real time to provide the stakeholder with the benefits of such analysis
- **Aggregated (batched) analysis:** a more complex form of analysis that is a lot more aggregated and has to run over all collected data
- **Key performance indicators (KPI):** it should be possible to define quantifiable outcomes as KPIs

(Fernández-Manjón et al., 2016, p. 22)

To systematize game learning analytics, Alonso-Fernández et al., consider the first step to be the use of a standardized format to exchange information between serious games and their analytics platforms, allowing for the development of reusable tracking components and easier sharing of data between analytics systems. (Alonso-Fernández et al., 2017, p. 1108).

The second step is the use of separate and standardized tools for analysis and visualization that allow game-specific customization if required. (Alonso-Fernández et al., 2017, p. 1108).

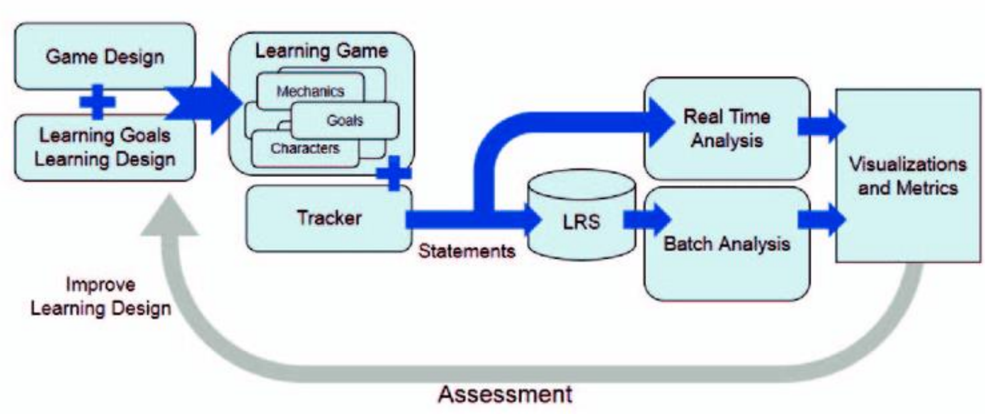

FIGURE 10: OVERVIEW OF GAME LEARNING ANALYTICS AS DESCRIBED BY ALONSO-FERNÁNDEZ ET AL. IN "SYSTEMATIZING GAME LEARNING ANALYTICS FOR SERIOUS GAMES".

The process of such a game learning analytics system is shortly described by Fernández-Manjón et al.:

> "The process starts in the game, which sends data to a collector. These data are sorted and aggregated, generating information to feed reports and visualizations (in real-time or not). This information is also used to assess students, and finally, the loop is completed through the adapter, that sends back instructions to the game to adapt it to the player." (Fernández-Manjón et al., 2016, p. 23)

6.5 RAGE ANALYTICS ENVIRONMENT

The RAGE Analytics Environment is a key component of the RAGE (**R**ealizing an **A**pplied **G**ame **E**co-system) EU H2020 project, developed as part of an EU H2020 SG-related project (Alonso-Fernández et al., 2017, p. 9) and is available as an open source project online[6]. It is an implementation of a game learning analytics system.

The tracking model was designed on an analysis of the state of data standards and serious games in combination with previous experiences made on applying e-learning standard to serious games. (Alonso-Fernández et al., 2017, p. 1108). The resulting model is described in the paper "Applying standards to systematize learning analytics in serious games" by Fernández-Manjón et al. The model keeps track of interactions through the use of events, that represent the interactions of players within the games. The event consists of the following attributes:

1. **Timestamp:** the point in time the event was generated

[6] eUCM Research Group, RAGE Analytics - https://github.com/e-ucm/rage-analytics

2. **User ID:** the player
3. **Action:** the type of interaction
4. **Target:** the game element that receives the action
5. **Optional value:** the parameter of the action

And aside from custom created targets and actions there are three types of targets in this model, that come with its own sets of actions:

1. **Completetables:** Deals with the progress of a player, has different scopes and can be started, progressed on and completed.
2. **Alternatives:** Deals with the in-game decisions of a player, consists of a set of options to choose and can be locked.
3. **Meaningful variables:** Deals with meaningful values during gameplay.

(Fernández-Manjón et al., 2017, p. 4).

To store the acquired information the Experience API is used, more specifically the serious game profile mentioned in section 6.1 and to fit this profile the interaction event fields are mapped to the profile attributes. (Fernández-Manjón et al., 2017, p. 8).

According to Alonso-Fernández et al. “this interaction model and its implementation in the xAPI standard provide a general, game-independent trace format that can model most, and frequently all, the interactions that a player makes with a SG” (Alonso-Fernández et al., 2017, p. 1108).

The RAGE Analytics Environment makes us of key performance indicators to allow educators to define relevant metrics, that assure that performance describing a player’s level of success is measured. (Alonso-Fernández et al., 2017, p. 1109).

Regarding the analysis and visualization of the collected data, the different users of the RAGE Analytics Environment have limited access to certain data and personal information that it contains, allowing teachers to see all of their students data and developers/researchers to only have access to anonymized and aggregated data. (Alonso-Fernández et al., 2017, p. 1109).

Furthermore, two design goals are supposed to be met:

1. Default sets of analysis and visualization, that provide insight without customization cost, are to be used, since no information on what kind of serious game is being played is produced.
2. Allowing advanced users to create dashboards and visualization depending on game-specific information, while minimizing the amount of configuration required and allowing for reusability of these assets.

(Alonso-Fernández et al., 2017, p. 1109).

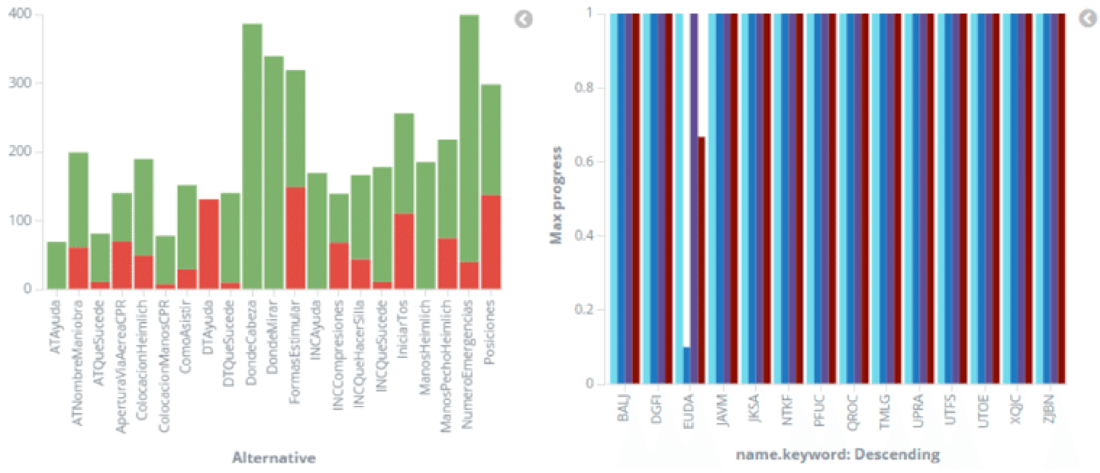

FIGURE 11: TWO EXAMPLES OF DEFAULT VISUALIZATIONS INCLUDED IN THE RAGE ANALYTICS ENVIRONMENT. THE LEFT SHOWS THE COUNT OF CORRECT AND INCORRECT ANSWERED ALTERNATIVES OF PLAYERS. THE RIGHT SHOWS THE PROGRESS MADE BY PLAYERS IN COMPLETABLES.

Alonso-Fernández et al. write the following:

> The analysis performed on the tracked data should focus on the suitable metrics and KPIs defined by educators, avoiding metrics that may confuse students or work against their learning process. Additionally, the default set of analysis of visualizations should also be adapted to the needs and interests of the different stakeholders involved in the process of GLA: teachers, students, game developers or designers, managers and researchers. (Alonso-Fernández et al., 2017, p. 1109)

The gathered data is stored in Elasticsearch[7], an engine that can “analyze and search a vast amount of data in near real time” (Alonso-Fernández et al., 2017, p. 1111) and the dashboards for visualization have been developed using the open source platform Kibana[8]. (Alonso-Fernández et al., 2017, p. 1111). The implementation of these dashboards allows for configuration and supports alerts and warnings to make it easier for teachers to support their students. (Alonso-Fernández et al., 2017, p. 1111).

[7] Elastic, Elasticsearch - https://www.elastic.co/products/elasticsearch

[8] Elastic, Kibana - https://www.elastic.co/products/kibana

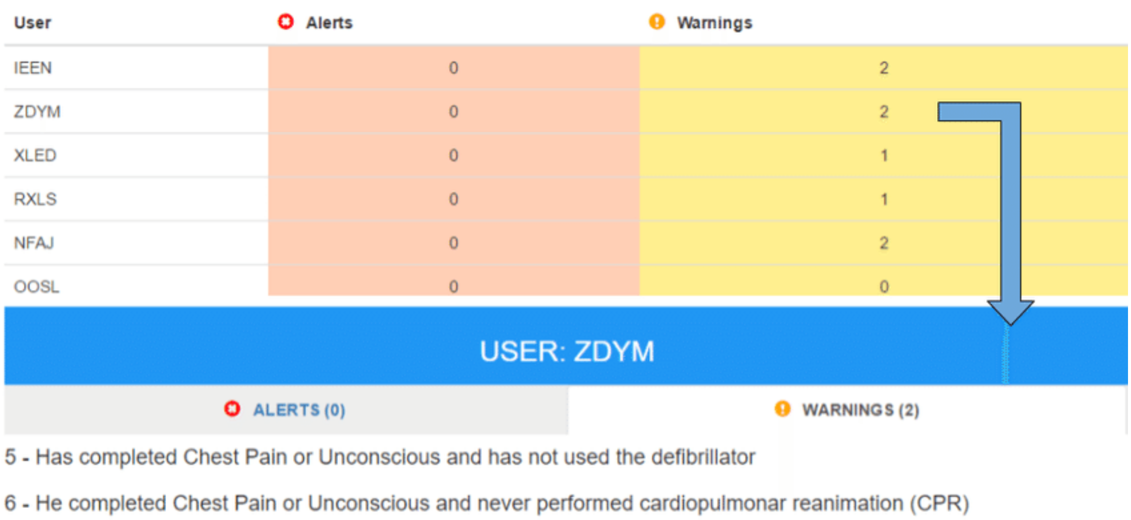

FIGURE 12: THE DEFAULT VISUALIZATION OF ALERTS AND WARNINGS IN THE RAGE ANALYTICS ENVIRONMENT, SHOWING THE GENERAL AND THE USER-SPECIFIC, MORE DETAILED VIEW OF ALERTS AND WARNINGS FOR EACH USER.

6.6 META-LEARNING ANALYTICS MODEL

Alonso-Fernández et al. built a Meta-Learning Analytics Model or short Meta-LAM, based on the GLEANER framework, mentioned in section 6.3, and requirements for a game learning analytics system proposed by Fernández-Manjón et al. in their paper “Game Learning Analytics: Learning Analytics for Serious Games”.

Alonso-Fernández et al. describe the problem in the original architecture and note that educational games might not consist of a simple game with one Learning Analytics Model, but instead are a combination of multiple games and components each requiring their own additional Learning Analytics Model related information, which describes how the player is learning and progressing within each part. (Alonso-Fernández et al., 2018, p. 1730). Even if each game and component has its own Learning Analytics Model, each of these focuses on its own game in isolation and, because of that, do not manage to describe the complete game as a whole. (Alonso-Fernández et al., 2018, p. 1733). And additionally, Alonso-Fernández et al. write about another occurring issue:

> Once several games are part of a larger aggregation, the problem of progress and completion as indicators arises: if there are several paths along the game, and some of them may require complex conditions that may or may not occur, it becomes very difficult to measure how much of the game remains to be completed. (Alonso-Fernández et al., 2018, p. 1733)

Because of these issues, Alonso-Fernández et al. propose their Meta-LAM model, that can “stitch together the individual game LAMs into a larger whole” (Alonso-Fernández et al., 2018, p. 1733). Each component will retain its own Learning Analytics Model and the Meta-LAM will describe how each of them joins together. (Alonso-Fernández et al., 2018, p. 1733).

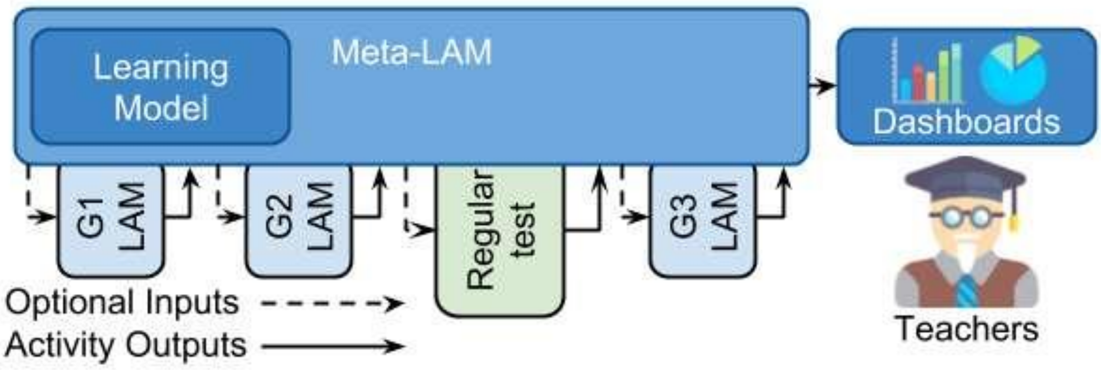

FIGURE 13: VISUALIZATION OF A LEARNING MODEL BUILT USING A META-LAM AND ITS RELATIONSHIP TO NORMAL, PER-ACTIVITY LAMS.

According to them a Meta-LAM should define a set of learning goals that the game as a whole has to achieve as well as how these learning goals are going to be achieved by its different games and components. (Alonso-Fernández et al., 2018, p. 1733). Additionally, it should define how the information is to be traced, analyzed and visualized. (Alonso-Fernández et al., 2018, p. 1733). Although the final Meta-LAM will depend on the hierarchy structure of the game, a general structure can be defined for simple hierarchies. (Alonso-Fernández et al., 2018, p. 1733).

To structure their model of a Meta-LAM, they used a greatly simplified version of the IMS Simple Sequencing specification. (Alonso-Fernández et al., 2018, p. 1733).

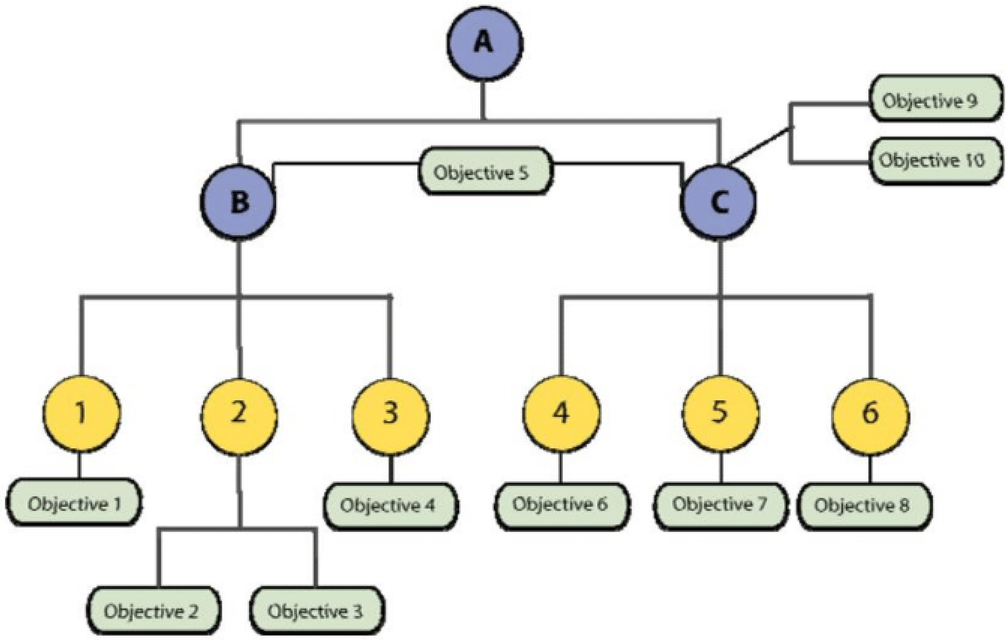

FIGURE 14: AN EXAMPLE OF AN ACTIVITY TREE FOLLOWING THE IMS SIMPLE SEQUENCING SPECIFICATION. THE NODES A-C AND 1-6 REPRESENT LEARNING ACTIVITIES, SUB-ACTIVITIES. OBJECTIVE 1-10 REPRESENT LEARNING OBJECTIVES.

According to them, the specification defines an Activity Tree as a main hierarchical structure. The tree consists of Learning Activities each having their own completion, mastery conditions, being able to contain sub-activities and can have one or more Learning Objectives. Learning Objective can be referenced by more than one Learning Activity. Clusters are learning activities that have immediate child learning activities. Rollup rules define how progress of clusters is evaluated and consist of a set of child activities that must be considered, conditions that have to be evaluated, actions that have to be taken and by default all child activities are includes in a parent rollup. (Alonso-Fernández et al., 2018, p. 1734).

They mapped this specification to their Meta-LAM to make use of it. The Activity Tree corresponds to the Meta-LAM itself. Learning Activities correspond to games or components, to make sure that each of them has a LAM as long as learning content to track and analyze exists. Each associated LAM will define the conditions for completion of the game or component. The Learning Objective correspond to the learning goals of the games or components. Rollup rules are essential for the Meta-LAM definition and define how information of children in the tree is aggregated for their parents. (Alonso-Fernández et al., 2018, p. 1734). And according to them "this hierarchy also allows for multi-level status storage" (Alonso-Fernández et al., 2018, p. 1734) and is required should a game launch multiple games in turn. (Alonso-Fernández et al., 2018, p. 1734).

Their implementation of this model uses the serious game profile of the Experience API to send traces. (Alonso-Fernández et al., 2018, p. 1735). For analysis and visualization, they use the tools of the RAGE Analytics Environment. (Alonso-Fernández et al., 2018, p. 1735).

In a later paper, called "Multi-level Game Learning Analytics for Serious Games", Fernández-Manjón et al. describe an architecture for the analysis of the Meta-LAM.

Their architecture uses stream-based analysis to analyze game traces in near real-time. (Fernández-Manjón et al., 2018, p. 3). The analyses get their data from a queue that contains the trace sent by the games and these traces are then analyzed only once by analyses that associate with the game. (Fernández-Manjón et al., 2018, p. 3). They describe how analyses can read and write, from and to datastores and additionally analyses are able to add new statements to the queue, allowing the queue to contain game-generated statements, always coming from leaves, and analysis-generated statements, informing "intermediate nodes of knowledge propagation within the hierarchy" (Fernández-Manjón et al., 2018, p. 3) and these statements move up the hierarchy until the root is reached, and by doing so create a message system with statements that target a node each. (Fernández-Manjón et al., 2018, p. 3). Once a child node is completed, the parent node adjusts itself so that when all child nodes of a parent node are completed, the parent node is completed as well. (Fernández-Manjón et al., 2018, p. 3).

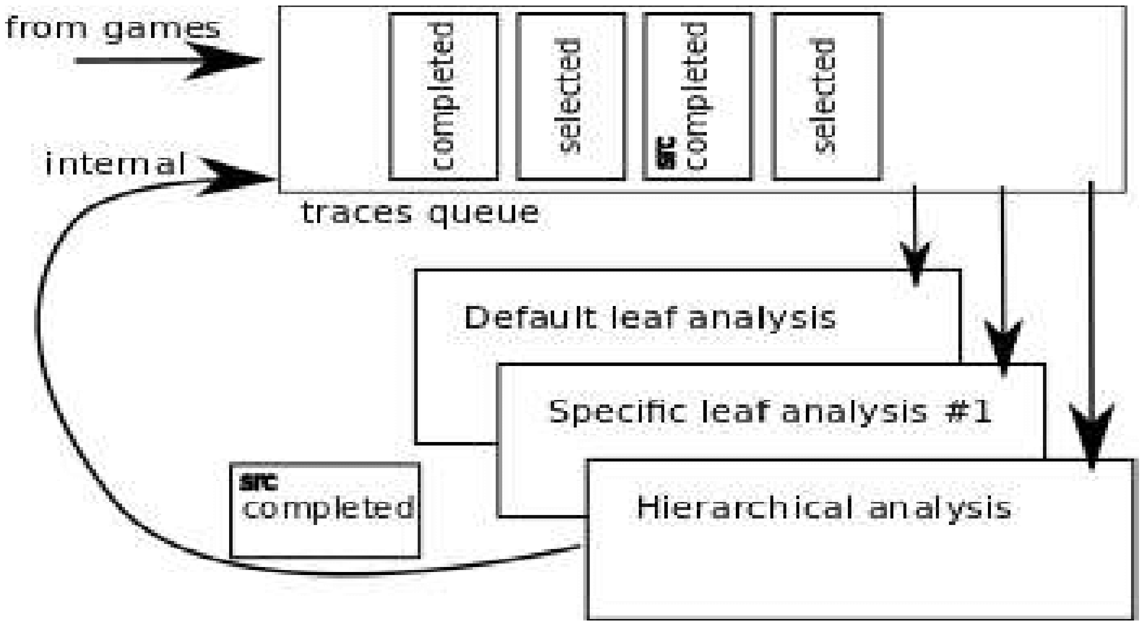

FIGURE 15: DIAGRAM OF THE CONSUMPTION AND BUBBLING OF TRACES IN THE MULTI-LEVEL GAME ANALYSIS.

For visualization they perform several types of leaf aggregation:

- Minimum, maximum and average of player scores
- Time-to-completion
- Completion history
- Choices taken
- Accuracy of choices
- Player progression

(Fernández-Manjón et al., 2018, p. 3)

They use multiple dashboards for their Meta-LAM instead of a single one, to allow users to navigate through the game tree and most visualizations are "intended to be meaningful both unfiltered and filtered-by-student" (Fernández-Manjón et al., 2018, p. 3). The root dashboard mostly adheres to the serious games profile of the Experience API, to allow for games to use this Meta-LAM to visualize analyzed data correctly as long as they follow the specifications of the serious games profile correctly. (Fernández-Manjón et al., 2018, p. 3). Fernández-Manjón et al. (2018) designed all visualizations to be as generic as possible (p. 3), as to not overwhelm teachers and other users and worsen the user experience (p. 4). Because of that their solution consists of five sections:

- **General information and configuration:** This section is designed to allow for quick access to information regarding the proper function of the lesson, allow the configuration of the dashboard and includes visualizations in the form of a student list for filtering, session counter for comparison, completion counter for student progress checking and time-frame selector.
- **Scores:** The scores section allows to see if player succeeded or failed and the overall performance of the player in each node.
- **Answers:** This section includes information on all choices a player made in each of the games.

- **Progress and duration:** The progress and duration section provide information on the progression and time taken of players overall and in each activity.
- **Location-based games:** This section contains information, in the form of a heat map, regarding visited locations and the time to get there, in case a game as multiple location-based minigames

(Fernández-Manjón et al., 2018, p. 4)

7 OPPORTUNITIES FOR IMPROVEMENT

Learning analytics in serious games has progressed a lot over recent years and although many improvements have been made in the field of learning analytics in general and in combination with serious games, there are still a lot of opportunities for improvement. This section will mention some opportunities that could improve learning analytics in serious games, that other authors mentioned in their papers as well as some that should be fairly obvious but come with some issues that hinder realization.

Despite the fact that many promising Learning Analytics Models for use in serious games have been proposed, a lot of serious game developers still use individually created solutions developed for a single or, in some cases, handful of serious games. (Alonso-Fernández et al., 2017, p. 10). Alonso-Fernández et al. suggest that learning analytics in serious games could "could greatly benefit from a general standardized approach" (Alonso-Fernández et al., 2017, p. 10) and according to them increase the use and development of serious games by "promoting quality through evidence-based iterative improvement and better evaluation; while minimizing GLA deployment and development costs" (Alonso-Fernández et al., 2017, p. 10).

Another relatively obvious opportunity for improvement is the general use of a specification that standardizes the transmission of game traces for analysis. This would make it possible to use collected information in separate, different systems and allow for sharing and use of data between institutions, researcher, teachers and developers, without having to translate data into a different format. Although the Experience API already allows for this it is probably not used or supported by most serious games.

Another point that could be improved is the integration or support of learning analytics architectures, or at least data collection and transmission, within game engines to allow the developers to use these architectures without having to spend too much time and money to integrate them from scratch on their own. The Experience API for example already has integrations in a couple of engines, like an asset for integration in Unity[9] , but integration in less well-known engines or the integration of parts of whole architectures is still lacking.

Another area that needs improvement concerns the use of visualization tools. Some authors mentioned that they encountered issues related to the interpretation of their dashboards by novice users, especially if they weren't involved in the design process of the game, and suggest a better explanation of the dashboards. (Alonso-Fernández et al., 2017, p. 11). It should be logical to assume that this will not just be an issue in this particular implementation, but rather an issue that many developers will have to address sooner or later, to make sure that users of their software have an easier time using and interpreting it. Furthermore, this is especially an

[9] GBLxAPI - https://gblxapi.org/community-blog-xapi-gbl/14-unity-3d-xapi-pilot-getting-started

issue when the serious games being used are complex and require custom methods of visualization to facilitate the assessment of learning within them. Fernández-Manjón et al. feel that "many teachers are already overwhelmed with relatively simple dashboards" (Fernández-Manjón et al., 2018, p. 4). And because of that visualization tools should be designed to allow for easy configuration and adjustments, to allow even instructors and other users without a technical background to configure the tool, if required, to their needs.

External hardware is also one of the possible sources of useful information, that is often not included in architecture and approaches concerning learning analytics in serious games. According to Göbel et al., the use of external hardware to get data, like biometric data, can help improve learning analytics in serious games. (Göbel et al., 2014, p. 23). For example eye trackers could be used to see what parts of the game the learner fixates on and this data, like heat maps, could be used to adjust the level or game design to make it more intuitive for the user or help the user to adjust certain behaviors. The data gained from hardware like heart rate sensors or respiration sensors, among many other ways to gain biometric data, could be potentially used in therapy to monitor the user and adjust the game accordingly.

8 OUTLOOK AND DISCUSSION

Learning Analytics in serious games is most definitely a fascinating topic and it is also most definitely worthwhile, since it provides:

1. Developers of serious games with knowledge on how their games are being played by its users as well as insight into the learning process of players and in the end can prove the effectiveness of the learning design in their games and improve and optimize the game design itself.
2. Teachers with a way to monitor the learning process of their students, allowing them to intervene if they see or have the feeling that a student requires help or has an issue with a certain topic as well as making it possible for them to give a student advice regarding a lesson when they need it the most.
3. Students with insight on how they behave and allowing them to find better ways to tackle problems and allowing them to learn certain topics, which otherwise might be rather complex to understand, more easily and efficiently in a rather playful, engaging and less stressful manner.
4. Researchers with the possibility to use gathered information to help with the analyzation of causation of certain behaviors and their correlation to other behaviors as well as the analyzation of the learning process itself.

And although the use of learning analytics in serious games is worth it, there are still a lot of points and problems that need to be improved as well as need more research and regulation. Like it is mentioned in section 5, the anonymization and the possible abuse of gathered data is probably one of the biggest issues that need to be addressed in future works. Some promising and somewhat standardized models exist, especially the RAGE Analytics Environment is one of the most promising ones, allowing for more or less easy extension, because of its modular components, as well as relatively easy integration since it is using the specification and serious games profile of the Experience API.

9 SUMMARY

This seminar paper gave an overview of the use of learning analytics in serious games. Starting with a short introduction to serious games and their comparison to normal, static learning materials. Mentioning the common ways and issues of validation of game design and learning within serious games, leading to the requirement of learning analytics to help and improve the validation process.

Following that ways to define learning analytics as well as the use of learning analytics in serious games and the suggestion that learning analytics should be combined with game analytics in the form of game learning analytics, requirements and suggestions for the collection and selection of data, different types, ways and suggestions on how data can be analyzed, visualizations and the need to adjust them depending on the stakeholder as well as the implication in form of requirements for the design of a serious game and the form of benefits learning analytics can have for game design were mentioned.

This seminar paper also mentioned learning analytics related fields, especially game analytics and educational data mining and their relation to learning analytics.

The concerns, issues and limitations were noted, ranging from ethical issues of the collection, storage and usage of data and the requirement for anonymization and the training required for teachers to interpret data in the right way, to the issues of large data storage costs and lack of standards regarding the use of learning analytics in serious games.

Additionally, some specifications, frameworks and models that show promise to simplify the use of learning analytics in serious games were mentioned. Starting with Caliper Analytics and the Experience API and its serious game profile, two specifications that can be used for transmission of data from the game to the analytics component and giving a short description of their structure. The GLEANER framework that can be used as a base for a learning analytics architecture. The Game Learning Analytics System requirements to increase the benefits and systematization of learning analytics in serious games. The RAGE Analytics Environment, a component of the RAGE EU H2020 project. That is based on the GLEANER framework and requirements for a Game Learning Analytics System and uses the serious game profile of the Experience API to deliver a learning analytics solution for use in serious games. And in the end the Meta-LAM model extending a normal Learning Analytics Model, explaining the tree structure that the Meta-LAM uses shortly and the later added analysis and visualization components used in the implementation of the model.

Second to last this seminar paper mentions some of the possible opportunities for improvement. Including the standardization of learning analytics architectures for use in serious games and the standardization of components/specifications used for transmission of data between the game and the analysis component as well as the requirement and need for simple to understand, use and configurable visualization tools and some of the benefits that can be gained through the use of external hardware, to collect data about the learner and environment they are in, outside of the game to complement and increase the accuracy of analyzation of data.

In the last section a short outlook and discussion on the use of learning analytics is given. Giving reasons for the worth of learning analytics in serious games and mentions the requirement for more research and improvements in the field of learning analytics in serious games.

10 ABBILDUNGSVERZEICHNIS

- **Figure 11:** Urheber nicht bekannt, (o. J.) o.T. Alonso-Fernández, C., Fernández-Manjón, B., Freire, M., Martínez-Ortiz, I. & Rotaru, D. C. (2017). Full Lifecycle Architecture for Serious Games: Integrating Game Learning Analytics and a Game Authoring Tool. Serious Games, pp. 73-84.
- **Figure 12:** Urheber nicht bekannt, (o. J.) o.T. Alonso-Fernández, C., Fernández-Manjón, B., Freire, M., Martínez-Ortiz, I. & Rotaru, D. C. (2017). Full Lifecycle Architecture for Serious Games: Integrating Game Learning Analytics and a Game Authoring Tool. Serious Games, pp. 73-84.
- **Figure 13:** Urheber nicht bekannt, (o. J.) o. T. Fernández-Manjón, B., Freire, M., Martínez-Ortiz, I., Perez-Colado, I. J. & Rotaru, D. C. (2018). Multi-level Game Learning Analytics for Serious Games. 2018 10th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games), pp. 1-4.
- **Figure 14:** Advanced Distributed Learning, (2009) Sharing Objectives Example. Advanced Distributed Learning. (2009). ADL SCORM 2004 4th Edition Sequencing and Navigation (SN) Version 1.1.
- **Figure 15:** Fernández-Manjón, B., Freire, M., Martínez-Ortiz, I., Perez-Colado, I. J. & Rotaru, D. C., (2018) o.T. Fernández-Manjón, B., Freire, M., Martínez-Ortiz, I., Perez-Colado, I. J. & Rotaru, D. C. (2018). Multi-level Game Learning Analytics for Serious Games. 2018 10th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games), pp. 1-4.

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12 SELBSTSTÄNDIGKEITSERKLÄRUNG

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