UNIVERSITY OF MACEDONIA
POSTGRADUATE PROGRAMME
DEPARTMENT OF APPLIED INFORMATICS

A SYSTEMATIC LITERATURE REVIEW ON LEARNING ANALYTICS FOR SERIOUS GAMES

Master Thesis

Papadopoulou Athena

Thessaloniki, 6/2020

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Papadopoulou Athena

Bachelor’s Degree in Computer Science, Hellenic Open University, 2011

Master Thesis

submitted for the partial fulfillment of the requirements of

MASTER OF SCIENCE IN APPLIED INFORMATICS

Supervisor
Xinogalos Stelios

Approved by three-member examination committee on 26/06/2020

Xinogalos Stelios	Satratzemi Maya	Evagelidιs Georgios
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Papadopoulou Athena

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Abstract

Serious games (SGs) intend to educate, train and inform other than entertain. SGs' engaging, goal-oriented nature encourages students to improve while playing. Although SGs have been increasingly adopted as a useful supplementary tool to the teaching and learning process, there are educational issues such as: a lack of understanding of how the students interact with the games, how the learning process actually occurs and therefore teacher's mistrust to use SGs as an assessment tool. Learning analytics (LA) is a solution to these issues as it infers knowledge about the effectiveness of the educational process. LA is a powerful technology which analyzes player's interaction in concerns with educational content. In order to apply LA there are three necessary steps: tracing the player's generated data while s/he is playing the game, analyzing the collected data and finally visualizing the results. The interactive nature of SGs facilitates the application of LA but data collected suffers from standardization problems as the generated data vary in range. This study presents results of a systematic literature review on learning analytics for serious games: including uses of learning analytics in serious games, learning analytics steps, methodologies and existing tools for incorporating learning analytics in serious games, barriers and open research questions.

Keywords: Serious games, Game learning analytics, Learning analytics, Game analytics, data analysis, data mining, visualization, monitoring tool, assessment, feedback, framework.

Acknowledgments

I would like to express my deepest gratitude to my mentor Associate Professor Stelios Xinogalos for his support, motivation, and patience. His guidance and contribution to the research and writing of this thesis have made the accomplishment of this project possible.

Also, I would to thank all my professors for the knowledge I have acquired.

Finally, I must express my very profound gratitude to my family for their support and patience through the process of researching and writing this thesis.

Tnank you

Apostole

Elpida

Anastasia

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1 Introduction

1.1 Problem – Research Objective

The digital evolution and extended use of internet lead to the rapid increase in the number of players. Some studies state that there are over 70% of children and teenagers all over the European Union and over 90% in United States that play video games (Freire et al., 2016). Another feature that contributes to the excessive use of the games is the proliferation of smartphones, tablets and other electronic devices that are used as game platforms. The success of entertainment games arouse interest of researchers in many fields like: medicine, economics, history, literature, mathematics, physics, engineering. These games with educational content and purposes are known as Serious Games. (Alonso-Fernandez, Calvo, et al., 2017).

Serious Games are *"digital games created not with the primary purpose of pure entertainment, but with the intention of serious use as in training, education, and health care"* (Loh et al., 2015a; p. 6-7). Their design principles are based on interactive, story-driven, pedagogical simulation and techniques that lead to maximization of players' immersion and interactivity. (*Story and Simulations for Serious Games_ Tales from the Trenches - Nick Iuppa, Terry Borst - Βιβλία Google.Html*, n.d.) SGs aim not only to teach and assist in acquiring skills such as strategic and analytical thinking, planning and execution, problem recognition and solving, decision making, adapting to rapid change and expertise training, increasing collaboration and negotiation, improving short and long term memory (Loh & Li, 2016), (Westera et al., 2008) but also to change an attitude and to arise awareness of a certain issue. De Freitas & Liarokapis (2011) declare that the combination of media in SGs reinforces the players' memory in assimilation of information and that is the reason of SGs success in educational scenarios.

However, when it comes to the application of SGs in educational settings as a trusted and powerful resource, some challenges appear to hinder this application. Those are the development cost of the SGs and their inherent complexity, the lack of understanding how the actual interaction among learners and SGs occurs, and the difficulties to measure learning outcomes so as to optimize and understand the educational impact of SGs on students/players. "*As Van Eck (2006) pointed out, we are not likely to see widespread development of these games ... until we can point to* *persuasive examples that show games are being used effectively in education*" (Loh et al., 2015a; p. 10)

Inherently, playing a SG generates vast amount of information and highly individualized data traces that reveal the player's interaction, choices, attitudes and performances. Though, high scores and performance do not necessarily insinuate effective learning. Therefore, SGs are confronting the discrepancy among the gaming process and the learning process which may grow larger as games provide freedom of movement and autonomy in concerns with contextualized problem solving, adventure games, self-directed learning and a respected range of nowadays skills related to today's knowledge workers (Hauge et al., 2014), (Westera, Nadolski, & Hummel, 2014).

The solution to overcome these difficulties is in the new discipline of learning analytics in combination with games which has a great potential to provide insight to better assess and understand how games affect education and training and that eventually will improve the use of games in education.

1.2 Goals – Objectives

The emerging field of learning analytics arouses expectation on gaining actionable insight to properly measure, assess, and improve performance with SGs. In order to deeply understand how SGs affect the learning process, as well as the skills and techniques that are acquired while playing, SGs need both to be used as an assessment tool and to assess their educational effectiveness (Freire et al., 2016).

Initially, it is necessary to determine learner's requirements and to establish realistic expectations about the learning process and outcomes. Learning analytics in games need strict pedagogical rules that outline the learning goals and correlate them with analysis and visualization and a suitable platform that enables the above execution (I. Perez-Colado et al., 2018).

The application of LA requires a sequence of steps to be followed: tracing player's generated data while playing the game, analyzing collected data and finally visualizing the results and transforming them to knowledge. In this context, issues like the level of game knowledge, stakeholders (developers, teachers, students) of the final visualization or amount and complexity of the data must be considered.

The goal of this thesis is to review studies and researches on learning analytics for serious games:

- Serious Games and their use as a tool
- The uses of learning analytics in serious games
- Learning analytics steps and methodologies
- Game analytics and their uses in game learning analytics
- Methodologies and existing tools for incorporating learning analytics in SGs
- Barriers and limitations
- Open research questions.

More specifically the systematically literature review aims to investigate the following research questions:

- RQ1: Could we identify patterns by applying LA in SGs so as to pre-establish an expert performance baseline and thus predict learning outcomes?
- RQ2: Could commercial games analytics be useful for serious game learning analytics?
- RQ3: Are there defined methodologies for implementing LA in SGs?
- RQ4: Are there any empirical studies for integrating LA in SGs?

1.3 Thesis Contribution

The goal of this thesis is to review and outline issues that must be considered when using Learning Analytics for SGs.

This review aims to concentrate issues which would be valuable for different stakeholders such as developers, teachers, and students.

- The combination of data mining and visualization techniques on learners' interaction data may lead to incredible outcomes for the developers. Most common is the improvement of SGs design (extremely challenging or easy situations in the game) (Alonso-Fernandez, Calvo, et al., 2017).

- Main target for the teachers is to gain insight into how students play, learn and improve their skills. Teachers' task may be simplified by the extracted data (Morata et al., 2019) and make the classroom management and evaluation more flexible (Freire et al., 2016)
- Students need to know their progress in the SGs. Self-assessment, motivation, and comparing their performance are important features in SGs evaluation (Freire et al., 2016).

Additionally, different approaches of data collection and analysis will be defined. The architecture behind the integration of learning analytics and serious games will be described analytically. Eventually, we will present case studies that implemented learning analytics with SGs and their actual outcomes.

1.4 Structure

The thesis is structured as follows:

The first chapter is the introduction of the research carried out.

The second chapter presents the theoretical background of the study and related work. More specifically, it presents serious games uses, the learning analytics steps and methodologies, the uses of learning analytics in serious games, the integration of serious games and learning analytics, game analytics and how could game learning analytics benefit from them, limitations for using serious games as educational tools and assessment tools.

The third chapter provides the methodology that was used for the research, the research questions, the planning, the literature research, and the selection of studies, quality assessment of studies, and data extraction and synthesis.

The results will be presented in chapter 4 using both a quantitative and qualitative analysis. The research questions will be analyzed.

Finally, chapter five provides conclusions, summary of the thesis, limitations of the study, and future work.

2 Bibliographic Overview – Theoretical background

2.1 Introduction

As aforementioned the easy access to internet and its available tools, and the widespread use of electronic devices lead to the change of educational settings in which learning actually occurs (Fournier et al., 2011). This increasing adoption of new technologies encourages the use of SGs in education. The highly interactive nature of SGs in contrast to traditional methods may consist a valuable source of data for learning analytics systems which eventually provide knowledge about the effectiveness of SGs and the learning process (Á. Serrano-Laguna et al., 2012).

However, SGs except from offering an engaging experience that fascinates students and their retention, have as well to offer an educational experience so as students acquire knowledge that is applicable outside the SGs (Harpstead et al., 2014). The learning context doesn't have to be so obvious to students, hiding it behind playing may motivate students and turn learning into a more enjoyable process (Minović & Milovanović, 2013).

Inherently, playing SGs produces highly individualized raw data traces that reveal the player's choices, behaviors and performances(Ali et al., 2017). These data may be obtained in several ways and formats and subsequently to be applied into suitable analysis for each stakeholder. An important step is to make this analysis understandable through visualization tools and provide real-time feedback to teachers and students in order to improve the learning process. Integrating Learning Analytics into serious games is expected to extract relevant information of the learning process from students' interaction data in order to infer whether the students are really learning or the SG is helping them to learn.

2.2 Serious Games

The concept of serious games (SGs) was first defined by Clark C. Abt in his book Serious Games (1975) (Breuer & Bente, 2010). There are several definitions for the term serious games but most of them agree on the main idea that SGs is the use of game technology for applications that have a main purpose other than entertainment. Zyda's definition (Zyda, 2005; p. [26]) for SGs is: *"Serious game: a mental contest, played with* *a computer in accordance with specific rules, that uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives"*. According to (Dörner et al., 2016; p. [3])a serious game is: *"A digital game created with the intention to entertain and to achieve at least one additional goal (e.g., learning or health). These additional goals are named characterizing goals"*. Breuer & Bente (2010) doubted the term 'serious games' because games are fun by their nature and that makes them not serious (oxymoron), on the other hand, all games are serious because players play them seriously (tautology).

Alvarez et al. (2011) found that 90% of SGs comprised of message broadcasters and only 10% include their primary purpose of skill improvement and training (Figure 2-1 depicts the difference between entertainment and SGs). Message broadcasters are not serious games (*Serious Games market, 2011*). Serious Games are expected to be designed with the following characteristics (or attributes):

- Clear goals
- Repeatable tasks for knowledge consolidation
- Monitoring of students' progress
- Encouraging increased time on task
- Adjusting the learning difficulty level

Players acquire skills and a new set of possibilities that are not easily taught in traditional teaching. Moreover, failure in the immersive and challenging environments have no consequences, that means that players can experiment and explore freely without feeling unsafe and through exercise eventually learn (Calvo et al., 2016). SGs are here to improve players' skills: critical and analytical thinking, defining and solving problems, planning and execution, team working, strategic thinking, and sharpen players' reaction to rapid changes (Loh et al., 2015a).

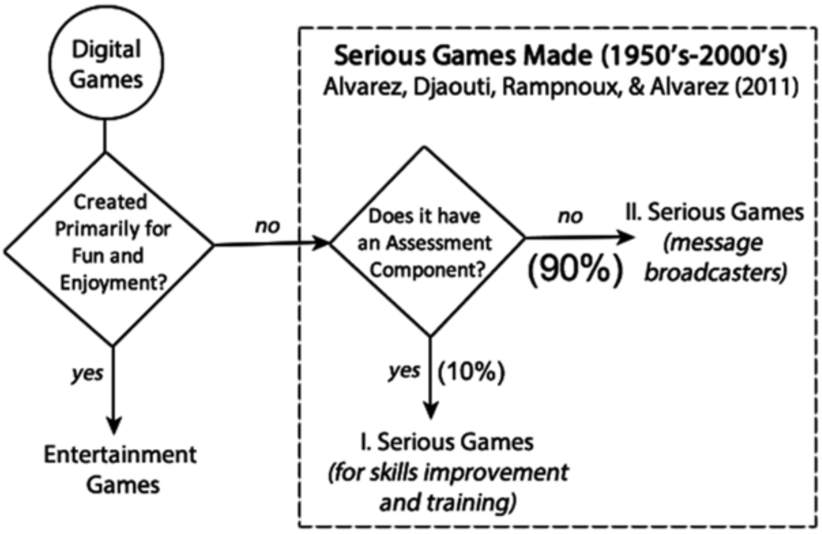

Figure 2-1: Difference between entertainment and serious games – (C.S. Loh et al.)

Nonetheless, the use of SGs in education arouses the necessity of deeper comprehension about how the playing affects the learning process and whether players acquire skills and improve their performances. Consequently, this need leads to the assessment of the SGs' effectiveness and the use of SGs as an assessment tool.

Playing SGs provides a vast amount of players' interaction data. SGs have to cooperate in an extensive and already settled educational ecosystem that is controlled by learning management systems (LMSs). Game incorporation in these contexts has been usually superficial, with a constrained communication with LMS. However, there is a need for a detailed inspection of players' interaction traces, since such examination will reveal valuable information about players' actions and the SG itself.

The use of SGs as assessment tools can help teachers to discover how students interact with the SGs, whether they misunderstand the content, or whether they obtain the objectives of SGs. The real time students' interaction data can provide the opportunity for personalization of SGs, adapting gameplay to a student and offer formative and unintrusive assessment and feedback. Although, SGs are powerful tools for teachers they won't rely on them for assessment purposes.

The detailed analysis of students' interaction may help in the improvement and creation of qualitative and effective SGs. Information obtained from these analyses, like difficult or extremely easy or boring points of the SGs may lead to desirable outcomes of learning effectiveness.

2.3 Gamifications, Game – Based Learning, Serious Games

The definition of SGs was already presented in Section 2.2. The term of SGs must be distinguished from the term Gamification and Game-Based Learning.

According to (Dörner et al., 2016; p. 7) *"Gamification means to add game elements to a non-game area, whereas games with a purpose denote games designed to exploit crowdsourcing in order to achieve a non-game purpose"*. Gerber (2012) (Loh et al., 2015a; p. 10) commented on, *"Often it seems that the spaces of edutainment and game-based learning get mixed with gamification"*. Loh et al. (2015a) in their study observed two tendencies of gamification. The first was that researchers tend to represent edutainment projects as gamification. The second is the effort to gamify e-learning with games, projects to enhance learning using animation and games instead of using game mechanics to motivate e-learners.

Qian & Clark (2016; p. 51) stated that *"Game-Based Learning (GBL) describes an environment where game content and game play enhance knowledge and skills acquisition, and where game activities involve problem solving spaces and challenges that provide players/learners with a sense of achievement"*. Game Based Learning can be resembled to Problem Based Learning (PBL), wherein specific problem scenarios are placed within a play framework (Ebner & Holzinger, 2007). GBL may be conceded as a teaching method where learners explore parts of games as a kind of learning in order to improve skills and achieve specific learning outcomes (Anastasiadis et al., 2018).

Nonetheless, SGs seem to be more suitable to provide the context for problem-based learning, probe learning, composition, association as SGs *"have more than just story, art and software...they involve pedagogy, activities that educate or instruct, thereby imparting knowledge or skill (Zyda, 2005)*" (Popescu, Romero, & Usart, n.d.; p. 6)

2.4 Serious Games as a Tool

There are many SGs developed for specific purposes as tools in military training, health area and education. Main objectives of these projects were to create tools for skills and performance improvement and to broadcast messages. In some cases the goal was to create virtual soldier experience with an informative nature for players, in other, to promote the importance of teamwork and to train players in simulation environment so as to improve strategic thinking and decision making, improving evaluation, prediction, monitoring, and educational process. In all cases SGs as a tool of education ought to reveal that the required learning has occurred.

2.4.1 Game for Skills and Performance Improvement

SGs as an educational tool have to obtain improvement of skills and performance of its play-learners through training and a set of instructions. While playing SGs a play-learner will "*play as they learn and learn as they play*" (Loh et al., 2015b; p. 14). The result of play-learning with SGs has to be except from knowledge acquisition, improvement of skills and performance of their players. The strength of SGs is to transfer the learning contexts into their environments and thus achieving "learning by doing". This aspect of SGs as improvement skills and performance tool arise the need of SGs analytics. SGs learning assessment has to be measured once the players' generated data are collected and analyzed.

2.4.2 Gameplay Data Collection

Gameplay data are the actions and behaviors that are performed while playing through players' interaction within the game. This interaction can be traced through variables while players perform course of action and achieve the goal. Repeated actions compose a behavior.

Gameplay data collection was considered a difficult issue due to several points but the rapid growth of mobile technology, social networking, datafication and easiness in information sharing, change human attitude towards data sharing.

More and more people are positive in quantifying their activities through different free applications. This conversion of activities into data is known as datafication (Loh et al., 2015a). Once activities are turned into data, "datafy", these data may be transformed into valuable information. Figure 2-2 depicts states from datafication of in-game actions to analytics.

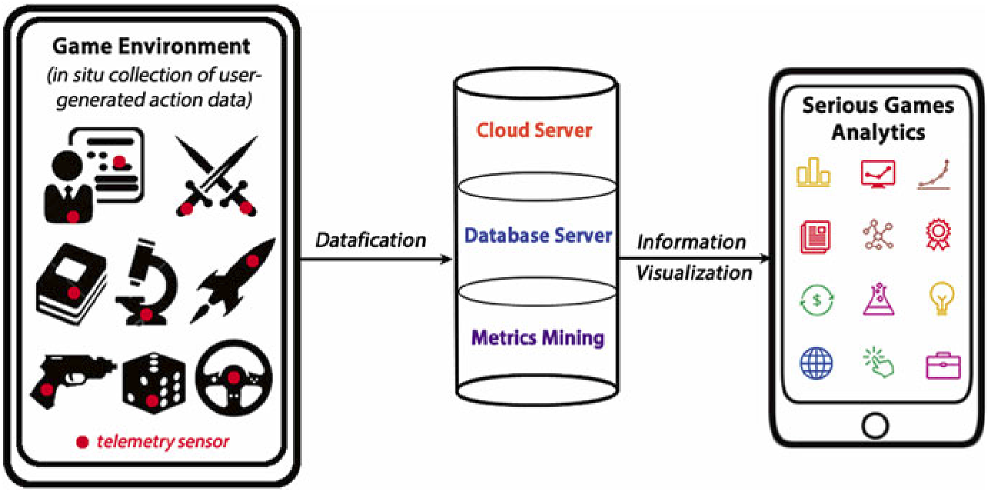

Figure 2-2: From datafication of in-game actions to analytics – (C.S. Loh et al.)

The gameplay data collection is quite similar to the aforementioned process. Players' generated data are "datafied" within serious games and are transformed into valuable information about skills and performance improvement.

There are two methods in collecting students' gameplay data: ex situ and in situ data collection. Ex situ data collection can be obtained from the outside world, out of the SGs environment in which the studying object or event take place. Such data are collected by surveys (demographic, feedback), interviews, focus groups, talking aloud, pretest-posttest analysis. This approach tends to treat SGs as black boxes: an indirect data collection cannot profoundly reveal how SGs content can actually affect students' performance while playing.

On the contrary, in situ data collection occurs within the game environment while students are interacting with the SGs. SGs programmers handle them as a white box because of the flexibility to manipulate the content and the in situ collection of user-generated data. In situ data collection eliminates subjective data and can be obtained by log files, game telemetry and information trails (Loh et al., 2015a).

Although, log data is generated within the SGs, that means it's in situ data, their analysis and exploitation occurs after the gameplay is completed. Thus, even this approach entails an ex situ assessment process.

Telemetry is the technique where players' interaction is directly traced within a digital game environment and is a necessary pace for SGs Analytics. Consequently, an in situ assessment process is feasible and may occur concurrently whilst gameplay is carrying on.

Information Trails originated in the instructional design stage, concerns with SGs assessment framework. This technique requires SGs to be online in order to use in situ data collection so as to enable ad hoc and post hoc assessment.

2.4.3 Limitations

Despite the increasing acceptance of SGs there are still some limitations that impede SGs from their adoption in education. Some of them are the high cost of SGs' development and maintenance, the SGs' learning effectiveness, and teachers' reluctance to utilize efficaciously SGs in their classrooms(Freire et al., 2016).

The complexity of SGs design process makes the development and maintenance of SGs an unaffordable project. Unlike the commercial games where development is extremely expensive but profitable industry, the SGs are funded mostly by government and research projects. However, the increasing interest to facilitate training and public awareness by using SGs seems a promising enhancement in the SGs' market.

The development and maintenance cost raise burdens in the creation of multiplatform SGs and the maintenance updates. Developing tools such as Unity3D, GameMaker Studio, Godot Engine, and Unreal Engine make the above issues easier, as these engines are almost free and don't demand deep technical and programming skills. Moreover, the created games can be exported in multiple platforms which means that the developer has to create the game once. This multiplatform development reduces the maintenance cost and working time. SGs could make the most of this functionality because of their flexible nature and the need to be adaptable to newer technologies and devices. Apart from technical and programming skills, the developers have to deal with graphical user interface, animation, music and with the most serious matter of an adequate instructional design.

SGs development is a highly interdisciplinary issue; it requires prosperous collaboration among developers and teachers and properly organized educational settings. In order to develop and deploy an effective tool for learning, several disciplines and technologies have to be taken into account; artificial intelligence, human computer interaction, computer graphics and architecture, networking, and others. These technologies are to contribute to the user oriented approach of the process and with the proper educational foundations; SGs are to provide quality content with desirable learning outcomes (De Gloria et al., 2014).

However, deploying SGs in classrooms meets some difficulties such as usability of developed games in existing operating systems and the connectivity with learning analytics platforms. Fortunately, the technological upgrowth and the easy use of internet make the use of SGs easier. Students may access and play SGs through browsers without the need of additional software installation and by their own devices, such as smartphones, tablets, etc. A crucial role in SGs adoption is in the teacher's hands. Teachers need to feel they have the control in order to introduce a new tool in their classrooms; they are reluctant in using SGs that they didn't develop themselves. They feel that using SGs won't let them to improvise and adapt lessons to their students' need. They have to deal with the suitability of the potential SGs and how to integrate them in their curricula. Most important, they need to know that their students learn as they play and if they improve their skills. Teachers may surmount the black box approach of SGs by retrieving data of the learning process and intervene when necessary. Learning analytics is the tool the teachers need to overcome these issues (Chaudy et al., 2014), (Freire et al., 2016).

2.5 Learning Analytics

Learning is an effect of interacting since learners interact with the teachers and with the learning content and with other students. Educators are concerned about designing their curricula in an ultimate way so as optimize and provoke as much interaction as possible. While designing their lessons they have to consider whether the planned interactions will be effective, and whether the course will be effective and will respond to the learners' needs.

Until few years ago a traditional measuring and evaluation of the aforementioned issues was an inefficient matter. It suffers from deficiency in data and from delay of reported data. Digital evolution and a trend towards online educational resources produces marvelous amount of interaction' data. The produced data can be easily tracked and stored and analyzed so as to improve teaching and learning (Elias, 2011).

However, the collection of every produced data is not wise for every stakeholder; it may cause storage problems and network traffic and has to be planned carefully, especially for gameplay data collection. On the contrary, web analytics collect online mainly text based data. These large sets of user interaction data are exploited by web analytics techniques and the analysis provides a valuable insight. Leaders, such as Google and Facebook are exploiting every single byte of the traced data for various reasons. For example, in commercial usage, the data mined after being processed may suggest products or targeted ads based on individual's location or demographic data so as to make them individually more relevant and useful. A close observation and analysis of big data sets through statistical evaluation facilitate the identification of distinguished patterns. These patterns aim to help in informed decisions taking and in construction of predictive models that will consequently improve the outcomes (Educause, 2010).

2.5.1 Learning Analytics definitions

Learning Analytics is a hardly new fast-growing field in technology-enhanced learning. It has roots in various domains, including business intelligence, web analytics, and Human Computer Interaction (HCI), assessment/evaluation, and research models in general. Ferguson, (2012; p. 4-5) defined three factors driving the development of learning analytics:

- big data – "*how can we extract value from these big sets of learning-related data?*"
- online learning – "*how can we optimize opportunities for online learning?*"
- political concerns – "*how can we optimize learning and educational results at national or international levels?*"

The vast amount of quantity and quality interactions data in the learning process lead to the analytics in education. There are several theories (fields) related to the educational data processing; the educational data mining (EDM), academic analytics, and learning analytics.

Educational data mining (EDM) relies mostly on automation and has to deal with the entire process of discovering knowledge from a large collection of complex educational data sets.

Academic analytics (AA) is the application of business intelligence in education; it reflects the role of data analysis at institutional level, identifies patterns that will inform academic issues and provide actionable decisions for academic management.

Learning analytics (LA) stresses on insights and interactions within digital learning environments, administrative systems, and social platforms concerning the educational information. This dynamic educational information can be exploited for real-time interpretation, modeling, prediction, and optimization of learning processes, learning environments, and educational decision- making in near real time (Loh et al., 2015a).

There are many attempts to define Learning Analytics but one of the most acceptable is: "*Learning Analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.*" (Siemens & Long, 2011; p. 2).

Generally most of the definitions emphasize on the collection and analysis of learning data and their conversion into actionable insight for improving the learning experience of the stakeholders.

Although, it is generally accepted that LA is the opportunity for improving the quality and effectiveness of learning, there are several issues that should be considered, continuous feedback of students' performance as compared with other students may discourage and demotivate them. Moreover, ethical and legal aspects, security issues, anonymization and ownership of information must be carefully considered (Wim Westera et al., 2014a).

2.5.2 Learning Analytics methods

A learning process generates digital trails while users/learners interact with mobile devices, learning management systems (LMS), and social media. The access logs of LMS leave a great portion of data points, including navigation patterns, reading and writing habits, and pauses. A close inspection of these logs may reveal behavioral patterns related to academic failure and propose remediation actions and real time intelligent adaptation.

Tanya Elias (2011), in her study about learning analytics definitions, processes and potentialities outlined that learning analytics have their roots in different disciplines but there are common processes for the application of learning analytics such as:

- Knowledge continuum, which is a conceptual framework for business, based on raw data and composed of characters, symbols and other inputs. It may answer questions like who, what, when, where. The information gathered after being analyzed can reveal actionable knowledge.
- Web analytics objectives, the main points in web analytics for educational purposes are to specify the goals, estimate the results, use the results for further improvement and communicate them for the benefit of others. In this way educators may achieve the desirable outcomes and find out new metrics for deeper outcomes.
- The five steps of analytics characterize academic analytics as a driver for decisions and actions. The five steps are: capture, report, predict, act and refine. The onset of this process is the gathering of the raw data as in knowledge continuum. After this, data is reported as information to enhance knowledge based prediction and action. In the final step, evaluation of the process takes place in order to improve and update the process. This may encourage the personalized learning establishment.
- Collective application model, this model has five layers which are parts of three cyclical phases and its purpose is to obtain knowledge discovery through representation of actions. It highlights the cyclical nature of analytics' process and the continuous necessity to refine and improve the systematic procedure by gathering, processing, and presenting information. In essence, LA consists of gathering, processing, and application. Gathering includes data selection and capture. Processing covers the information' aggregation and reporting, and the predictions based on that information. The last step, application involves the use, refinement and sharing of the acquired knowledge.

According to Tanya Elias (Elias, 2011) from the combination of these models and frameworks derive seven related processes of LA as shown in Figure 2-3.

Knowledge Continuum	Five Steps of Analytics	Web Analytics Objectives	Collective Applications Model	Processes of Learning Analytics
		Define goals	Select	Select
Data	Capture	Measure	Capture	Capture
Information	Report		Aggregate	Aggregate & Report
Knowledge	Predict		Process	Predict
Wisdom	Act	Use	Display	Use
	Refine			Refine
		Share		Share

Figure 2-3: Comparison of LA frameworks and models – (Elias, 2011)

Siemens (2013) stated that LA methods have two overlapping components: techniques and applications. Techniques deal with the specific models and algorithms that are used for the analysis of the educational data, whereas applications refer to the ways the techniques are exploited so as to influence and improve teaching and learning. The distinction between the two components is not absolute due to the overlapping.

There are five primary areas of the technique dimension:

- Prediction
- Clustering
- Relationship mining
- Distillation of data for human judgment
- Discovery with models.

The techniques dimension stresses on technical orientation by means of machine learning and artificial intelligence methods, statistical analysis and neural networks and so forth. The data based information of this process will provide meaningful insight of learner behavior and of applications as real time interventions, recommendations, predictions and of the models' creation which will identify learners progress and patterns, and predict students' performance.

The application dimension consists of the following five areas:

- Modeling user knowledge, behavior and experience
- Creating users profiles
- Modelling knowledge domains
- Trend analysis

– Personalization and adaptation

Application areas may leverage the development of curricula by adapting learning content to the students’ needs and profiles, by improving the designed courses. In addition, social network analysis (SNA) may help to identify patterns and to understand how groups within the classroom formed and how these groups collaborate and how they are affected from the courses’ structure and tools. The multidisciplinary nature of LA and the techniques and applications are presented in the Figure 2-4 and extended analytic techniques and applications are shown in Figure 2-5.

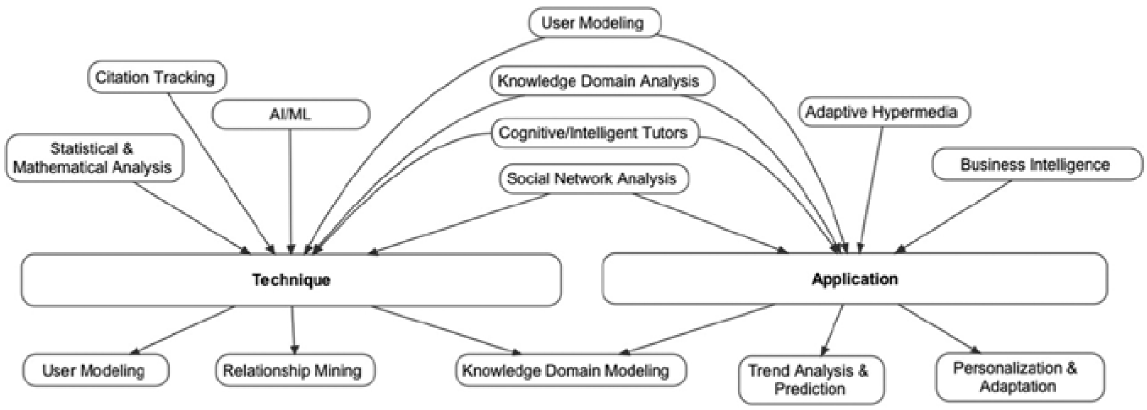

Figure 2-4: Historical influence of LA development – (Siemens, 2013)

LA Approach	Examples
Techniques	
Modeling	Attention metadata
	Learner modeling
	Behavior modeling
	User profile development
Relationship mining	Discourse analysis
	Sentiment analysis
	A/B testing
	Neural networks
Knowledge domain modeling	Natural language processing
	Ontology development
	Assessment (matching user knowledge with knowledge domain)
Applications	
Trend analysis and prediction	Early warning, risk identification
	Measuring impact of interventions
	Changes in learner behavior, course discussions, identification of error propagation
Personalization/adaptive learning	Recommendations: Content and social connections
	Adaptive content provision to learners
	Attention metadata
Structural analysis	Social network analysis
	Latent semantic analysis
	Information flow analysis

Figure 2-5: LA Techniques and Applications – (Siemens, 2013)

Learning analytics confront the big data problem where intelligent data mining techniques tends to identify subtle correlations. The widespread introduction of virtual learning environments (VLEs) and massive open online courses (MOOC) contribute to this aspect of LA as a big data problem because students interactions generates big data sets and favor any kind of automation. This arises the need for standardizing learning analytics. Learning objects have always been tracked by LMS but have evolved into complex interacted assets. The instructional management system (IMS) and common cartridge and sharable content object reference model (SCORM) may contribute to standardize these complex assets of reporting and to enable the use of an enriched interactions' model that will facilitate the collection of additional data of analytics-oriented interactions in more abstract form (Freire et al., 2016).

2.5.3 Game Analytics

Digital games are created for entertainment purposes. Consequently, Game Analytics (GA) involves metrics that aim to improve the game development and game research, so as to gain knowledge on users' gameplay which will finally give the chance to improve the gameplay experience. Some metrics cover: correct game balance, better game design, identify hidden problems, relieve bottlenecks, categorize game contents by players' preferences, distinguish players' types, and recognize new opportunities for post sales revenues (Loh et al., 2015a).

The key element in an entertainment game is to be aware how players/customers actually play and this insight will lead to the improvement of players' experience which in turn will lead to the monetary profits. Game analytics systems may collect any types of data. These data have two aspects: the technical refers to the game and its infrastructure and the other stresses on user data and experience.

The technical aspect has to deal with the metrics of the game development process which includes bugs in the games' code, fixation time, and the bugs' tracking within new versions. Also, while testing and deploying a game, records of performance metrics such as rate and memory usage of the devices disclose hardware and software bottlenecks.

On the other hand the user oriented aspect involves metrics that originated from the players' interaction with the game. Such metrics include customer metrics, community metrics, and game metrics. Customer metrics compose of transaction and purchase data of player, in or out of the game. Community metrics measure the players' interaction with other communities, like forums, customer services, etc. Game metrics measure all the direct players' data interaction with the game, such as hours of continuous play, return frequency to game server, subscription length for multiplayer online games (MMOGs) and many more.

The interactive nature of games generates vast amount of data, even, a short gameplay session. These data may be used to reproduce players' course of action. As in learning analytics, the game analytics apply data mining and visualization techniques to the players' interaction logs in order to gain meaningful insight of players' reactions with the game. Game telemetry (the remote collection of data) is used to develop perceptual measures through combining player behaviors and game states. The above analysis may reveal stumbling points, excessively easy or excessively difficult points of game and help developers to outcome these points.

Analysis that focuses on detecting unreachable areas that players never visited or popular areas where more interaction take place and more time is spent or unexpected software game errors occurs, help developers to assume the right moment for micro transaction suggestion or for targeted advertisement and thus lead the game improvement and sales growth.

Game analytics techniques have developed from learning analytics but include different goals and vocabulary. The main purpose of game analytics is to improve gameplay and turn the game to an enjoyable activity, improve game design and create attractive content so as to increase sales revenue. Nevertheless, both game and learning analytics have the same objective, games with better user experience. There is a noticeable interest among psychological and educational researchers for adapting digital games in classroom assessment. Systems like ADAGE (assessment data aggregator for game environment) and click stream telemetry data framework provide respectively the acquisition of in game data on play and learning, and the vision of games data stream. Game designers try to focus on stealth assessment; this means that any interaction may be extracted for assessment purposes. Therefore, games can be used as assessment artefact and to be assessed for educational effectiveness (Freire et al., 2016).

2.5.4 Game Learning Analytics

The primary purpose of serious game analytics is to acquire actionable insight to improve game and learning design and to improve players' skills and performance so as to prove game effectiveness. Game Learning Analytics (GLA) involves the analysis of students' interaction data which infer knowledge about the students' learning process. The educational objectives of LA and the technologies of GA may be used in combination to contribute to the creation of SGs. However, the combination of two disciplines does not absolutely constitute GLA but may contribute to generalization and better use of SGs.

According to Loh et al., (2015a; p. 23) serious games analytics is the *"actionable metrics developed through problem definition in training/learning scenarios and the application of statistical models, metrics, and analysis for skills and human performance improvement and assessment, using serious games as the primary tools for training"*. SGA come from players' gameplay traces and the visualization of players' course of actions, behaviors, and paths within the game environment. The obtained data is the key to associate gameplay with actual learning and provide a step to move forward from theory based approaches to data driven or evidence based approaches and finally to contribute in gaining knowledge of how the learning process occurs.

In order to obtain analytics from player generated data the following steps have to be applied:

- Tracing player's generated actions while playing the game. This interaction data provide evidence for players' skills and aptitude and their subjective process.
- Analyzing the course of actions by means of machine learning and statistics.
- Finally visualize the results and transform them to knowledge

As aforementioned, before the SGs design and implementation, it is necessary to clarify educational goals and establish realistic expectations about the learning process and outcomes within the gameplay. Learning analytics in games need strict pedagogical rules that outline the learning goals and correlate them with analysis and visualization and a suitable platform for execution. Thus, the intended educational goals provide guidance on the GLA' development which define the data analysis and visualization results. Figure 2-6 depicts the steps for using videogames as classroom exercise.

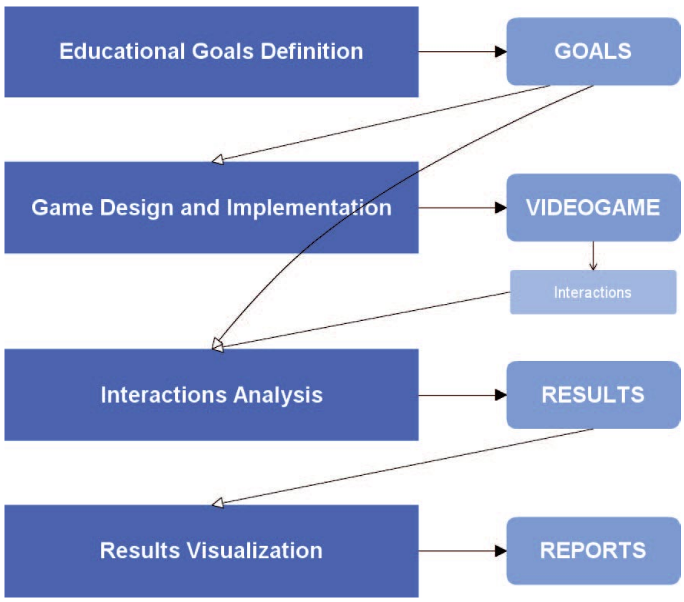

Figure 2-6: Steps for using videogames as classroom exercise from A. Serrano-Laguna & Fernandez-Manjon (2014)

2.5.4.1 Data collection

Data collection comprises the initial step of the GLA process. It is necessary to determine what should be tracked, but it is also wise to collect all kind of activities as they may be useful from an analytics perspective. Additionally, the data collection requires high availability and bandwidth utility that will not miss a single incoming trace under any circumstances (e.g. bottleneck) and eventually be traced. The data that is going to be collected may be possibly classified by the desired quantity or quality. The extensive data refers to data collected from large number of users with limited user information. On the contrary intensive data produced by focusing on a limited number of users can be used to derive deeper and detailed information. Extensive data contribute to patterns recognition in big data sets for educational data mining (EDM) and intensive data performs recognition of one and the same user over among different data streams but when combined may ensure that almost all patterns will be recognized.

Collecting interaction data from a collaborative leaning environment within an LMS or a multiplayer SG can help to detect aspects of collaborative learning over relations and structure. There are basic sets of interaction traces that can define: generic and game-specific traces. Generic sets of traces consist of game traces, phase traces, meaningful variable traces, input traces.

Game traces refer to timestamps like starting, quitting, ending a game and to users' identification and demography. Game ending reveal information about how many times the game was ended, if the game was completed, or quitted, etc.

Phase traces deal with starting, ending phases through narrative chapters, mission or phases and reveal successful completion, time spent, etc.

Significant variables traces can reproduce the students' gameplay. Usually, they contain a state of the game, scores, etc.

Input traces are input sources, type of actions and associated data.

Generic game logs provide valuable insight about the SGs assessment and may contribute to the detection of game design strength and weakness (Á. Serrano-Laguna et al., 2012), (Shoukry et al., 2014).

In some SGs there is a need to track specific players' interaction that cannot be tracked with generic sets of traces. There are many reasons for this kind of tracking interactions (e.g. to facilitate manual subjective analysis, tracking chat logs). However, to avoid the loss of automation in processes, the use of custom interaction must be restricted (Á. Serrano-Laguna et al., 2017).

The process of data collection must not be visible to the students, since it may have a negative influence. One of the mining tools that is tracking silently and directly the players' interaction within a gameplay session is the game telemetry. The game telemetry collection aims to develop significant measurement from the combination of players' performance and game state.

In situ data collection occurs within the gameplay environment and thus eliminates the subjective data and can be obtained by log files, game telemetry and information trails. Event listeners and event tracers which are triggered by gaming and learning events are necessary for serious game analytics (Loh et al., 2015a).

An in situ assessment process is feasible and may occur concurrently while gameplay is carrying on. A real time analysis facilitates dynamic adjustment of the learning process and offers to teachers the opportunity to manage their classroom in place. Moreover, the collected data may be analyzed after the game is over, and this provides information to designers and developers to identify patterns and improve the game and gain knowledge for better future plans.

All the tracked data is collected and stored in a Learning Record Store (LRS) (Figure 2-7). The LRS theory comes from the e-learning domain as a database system to store statements in sequential order. It allows authorized and authenticated users to save and query traces (Alonso-Fernandez, Calvo, et al., 2017).

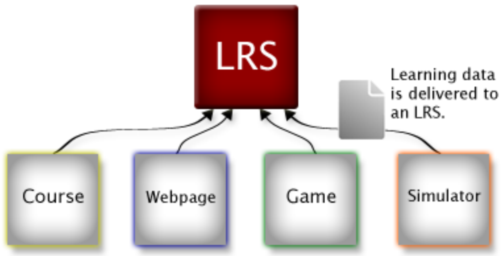

Figure 2-7: Learning Record Store from scorm.com

Once the collected data is stored it has to be processed and cleaned. The data cleaning process usually includes removing duplicates or external data or filling missing data. After the cleaning process of raw data, the database can be exported to an XML or flat file or CSV and proceed to further analysis by being imported into any suitable statistical program (Loh et al., 2015a).

The key in collecting the right data is to determine the learner's requirements, and to establish realistic expectations about the learning process and outcomes, and to identify which players' course of actions and behavior improve their performance. Knowing the SGs' structure gives us the ability to clarify the level of detail for the data that have to be collected - in some phases more detailed data may be needed to track and in others not. Thus, the SGs content and the data collection have to be designed carefully in order for SGs to be suitable for learning and training and the collected data to be relevant and meaningful. In addition, metrics such as achievements rate including scores, points gained, completion may be more significant as they reveal mission achievement or level completion in a given timeline.

Finally, the data collection arise awareness of applicable personal privacy laws and regulations. As it has to do with personal data, issues like anonymization, ownership of data, the use of data, who and how is going to use the collected data and for which purposes must be clarified.

2.5.4.2 Data analysis

After the data is being collected from different players and sources, it has to be merged for data mining or statistical processing. In addition, intensive data has to be aggregated for combining multiple streams for the same user but from different devices. Logs typically contain large amount of data that has to undergo several processes, like structuring, segmenting, filtering and normalizing raw data. According to (Shoukry et al., 2014), there are aggregation models that use semantic rules to map game actions or states to meaningful expressions where similar events are grouped. During the aggregation phase, synchronizing data is essential for detecting behaviors at specific timestamps across data streams and for analyzing situations, verifying claims and coming to conclusions.

After the aggregation stage, data can be used for reporting. Automatic analysis of data becomes more complicated because in educational games, real time processing is required for personalization. There are two perspectives, the learning and gaming. From the learning point of view the collected data should reveal information about learners' general characteristics and abilities, their general knowledge state, their situation specific state, their learning behavior and learning outcome and from the gaming point of view the collected data shall reveal game performance, in game learning and strategies (Shoukry et al., 2014).

The learning analytics processor performs the analysis on the collected data. Data from LRS, LMS or other systems are transformed in an appropriate format and loaded to the processor. Then, the analysis is executed; according to needs it could support academic or predictive analysis. Finally, the results are performed for further computation or storage or visualization through APIs (application programming interfaces) web services.

The performed analysis could be general or game specific analysis and could either be performed to the data of players' groups or to a single student's data. General analysis includes the number of students that complete each level, the completion time for each level, the final ranking of each students correlated to the other students of the class or of the game generally. Game specific analysis refers to the particularities such as SGs characteristics and its specific learning outcomes. These analyses provide more detailed information of particular session and reveal students' advancement, errors or learning skills.

Cluster analysis help in identifying solution strategies and error patterns of students and general profiles. Students' behavior profile is important because their in-game actions may compose patterns. Data mining and behavior categorization techniques reveal these patterns that can be exploited to develop students profile afterwards. Students may be classified according to age, gender, demographics, etc. This analysis may contribute to the prediction of players' in game behavior and thus avoid students' failure when misleading patterns are detected. Exploiting information gained from this approach, SGs could be designed to support personalized and adaptive player experience (Loh et al., 2015a).

2.5.4.3 Data visualization

The main purpose of visualization is to transform data into knowledge in an appropriate way, as the visualization of results is essential for understanding them. The collected data come alive when there is an efficient and effective way to visualize and explore it. The extracted information from the collected data shall be communicated in a clear and transparent way which can be obtained by graphical representations like tables, charts, histograms, scatter graphs, etc. Except from real-time feedback for students and teachers, differences among individual students and groups are visible. (Loh et al., 2015a)

According to (Tlili et al., 2015), Khan and Khan defined two types of visualization: data visualization which is the presentation of data in a visual form by means of tables, charts, etc. and information visualization which is again the presentation of data in a form which allows deriving information from the association among these data. This may be achieved by using diagrams such as entity relationship and data flow, and semantic networks.

The visualization of analytics through the graph forms provides a wide range of information such as the current students'/players' state at a particular moment, progress, in-game actions/interactions, scores, completion, generally, an overview of key indicators and more specific game information (Morata et al., 2019).

It is important to consider at an early stage of the design process all necessary information so that the visualization results are clearly understandable. Stakeholders should be able to know what is shown on the graphs and how these results are obtained and why. Stakeholders may be classified in the following groups:

Students/players: in this case visualization may provide feedback for their performance, their scores and achievements. It may also present their progress in comparison with their co-players or with historical gameplay. This may have positive results in students' performance; increase the sense of confidence, collaboration and competition.

Teacher: there are many benefits for educators that can have an overall view of their classroom during the gameplay, as well as intervene where needed. General statistics such as the number of students that finished the game; the levels, time spent, mistakes made and in-depth information for each student are available. The monitoring of students' progress offers to teachers the opportunity to adjust the learning process to their students' need.

Developers may benefit from data visualization for the improvement of the game design and for the pedagogical game effectiveness. General statistics about the game use and more specific information like stumbling points or excessively easy points of the game are useful for the improvement of the game design. Moreover, visualization can contribute to the design of games that will take into account the needs of different groups.

Apparently, the visualization results can be used differently for different stakeholders, including developers, researchers, instructors and learners. Personalization and adaptation to students' learning environments, students' progress evaluation or prediction of the best course of action are some of the valuable outcomes of the collected information. However, as it has to deal with personal data, issues like anonymization, access level to these data must be carefully considered. Developers shall have general information of users' game session. Teachers shall have access to detailed information of each student but students shall have access to their personal results and to some class metrics to compare their achievements.

The most impressive visual information is real-time visualization for teachers. Dashboards depict:

- The active players’ number, which in turn reveals if there are students that aren’t playing.
- The number of students who completed the game, that shows who came to the end or not.
- The number of levels completed which shows each students progress.
- Occurred collaboration in-game and many other metrics.

Some of the metrics are shown in Figure 2-8.

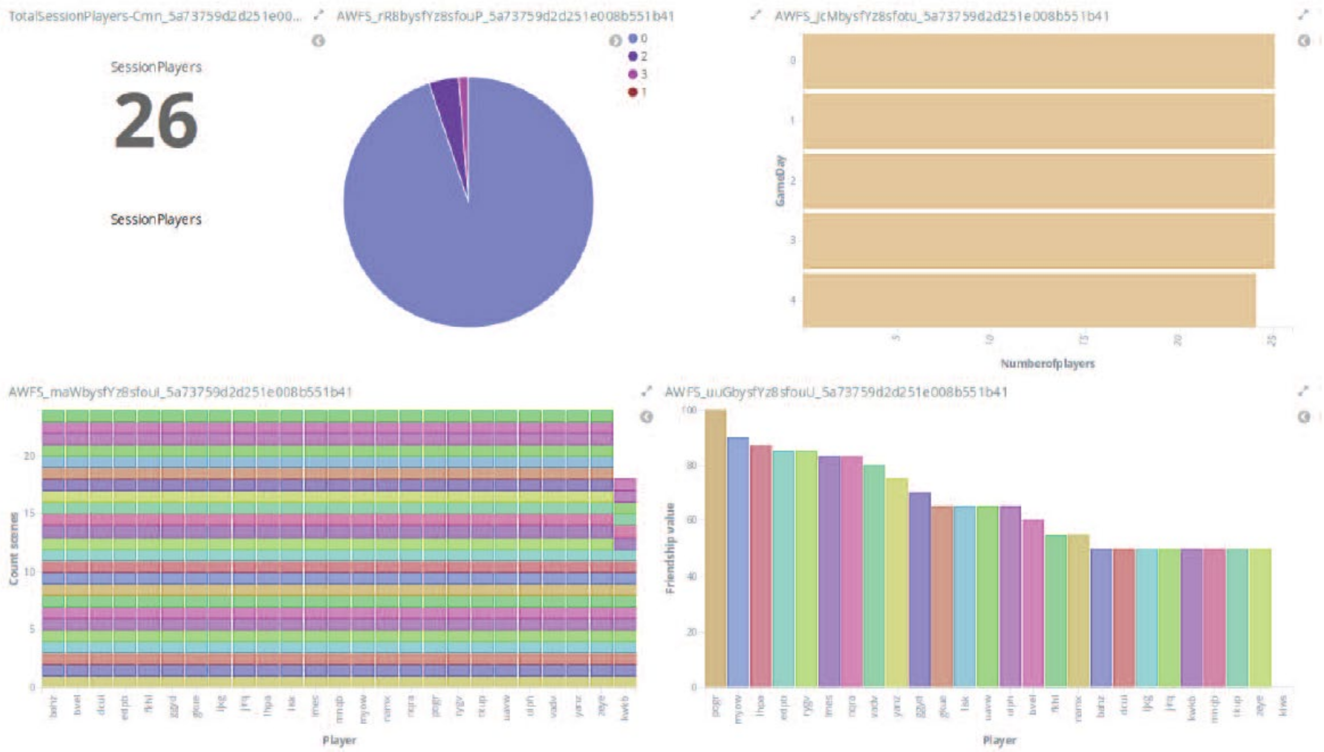

Figure 2-8: Sample dashboard to show information for teachers while games are in play (Morata et al., 2019)

Worth to mention is the alert or warning messages that have been included in early stage of the game design. These messages are triggered by pre-specified conditions and help educators to intervene in the moment that students need them to overcome difficult points or for those students who perform too fast and complete the game, educators may assign to them complementary tasks (Morata et al., 2019).

Minović & Milovanović, (2013) based on the fact that games are dynamic learning environments and that the educators must have real-time analytics on their students' progress, proposed a specific form of circular graph for the visualization of students' progress information. This compact way of visualization includes all the necessary information for educators. The point was to visualize the learning condition for one student, or for a group of students, having as a base specific visualization of a student model as shown in Figure 2-9. This visualization is based on Andersons Taxonomy Model which is a classification of learning objectives in the educational domain and consists of the following taxonomic levels: remembering, understanding, applying, analyzing, evaluating, and creating.

The center of the circle depicts the total learning progress. There is an interaction between total learning progress and neighboring progress concepts. All domain concepts are affected by neighboring concepts. Thus, make the information of overall knowledge visible by one cycle graph. The color scale changes from red (0%) to green (100%), the switch in color change takes place when a predefined passing number is reached.

The first level ring depicts the learning progress according to Anderson's taxonomy model. It concentrates on students' progress by showing levels with particular learning path. The ring is filled in with color while students interact with the learning path and different learning and assessment objectives.

The second level ring shows information of learning progress for the student, having calculated the students' performance through the learning path. It can be used for a group of students showing an average percentage of achievements.

The third level ring uses Anderson's model to represent separately neighboring domain concepts based on the second ring level. This rate is dynamic as it has an important role in higher cognition levels.

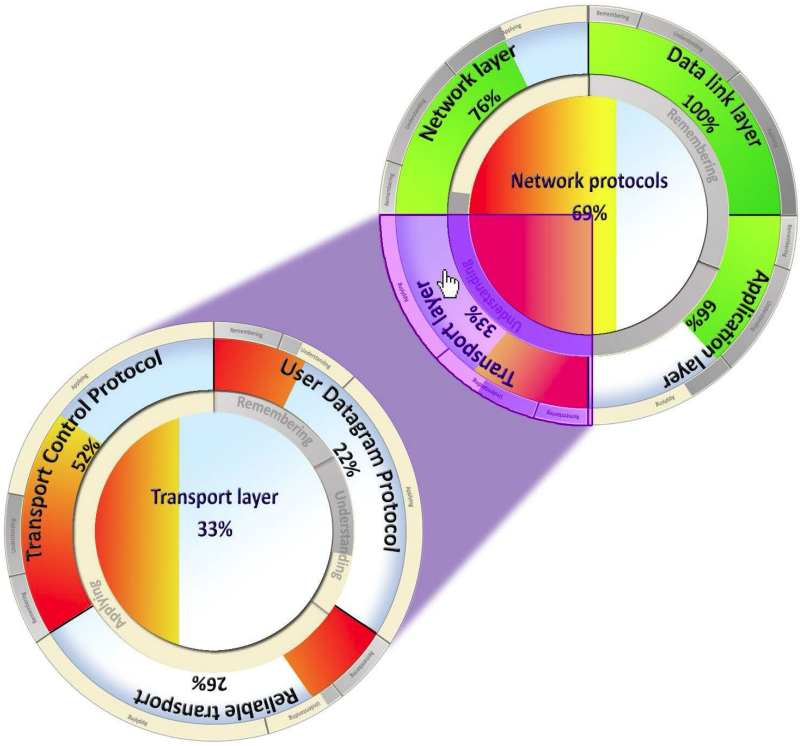

Figure 2-9: Visualization of student's knowledge (Minović & Milovanović, 2013)

The above cyclical graph represents all the necessary information of students' learning progress in a particular game session. Moreover educators may delve into more information in dubious concepts for the student by expanding every wanted part of the cycle.

2.5.5 Architecture

A Game Learning Analytics (GLA) system outlines a sequence of jobs that have to be done, including data collection, analysis and visualization. GLA architecture consists of modules that are shown in Figure 2-10: *"from learning goals, learning design and game design; the tracker embedded in the game sends Experience API (xAPI) statements to a Learning Record Store (LRS) for batch analysis, and directly to the real-time analysis. Some visualizations and metrics may be derived from the analysis to obtain further information for students' assessment and learning design improvement"* (Alonso-Fernandez, Calvo, et al., 2017; p. 7).

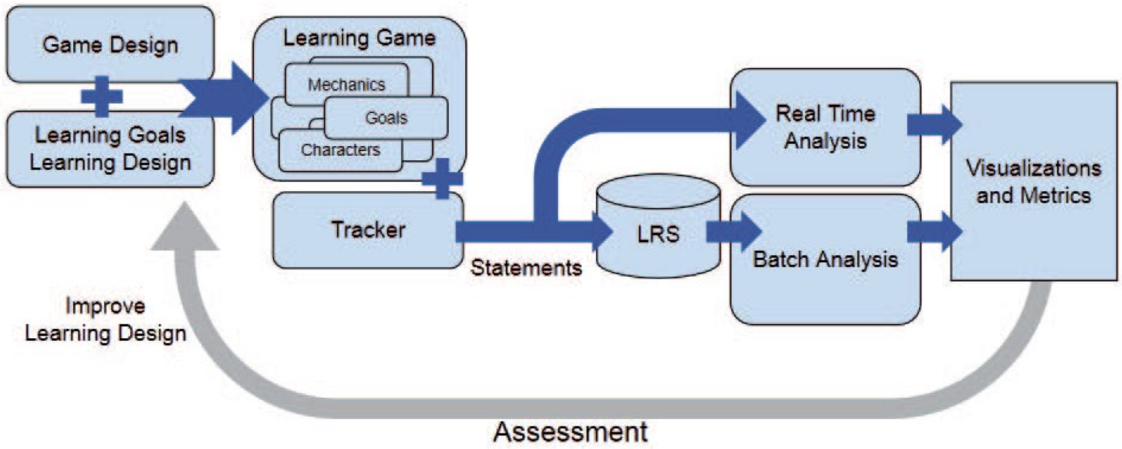

Figure 2-10: Overview of Game Learning Analytics (Alonso-Fernandez, Calvo, et al., 2017).

These models have to cooperate to reach the final step of results' visualization.

- Game design together with the learning goals and design make the learning game. Game and learning design are critical because in this phase education goals and elements are determined by means of variables. These variables will show if the learning actually occurs.
- Usually games embed generic tracker components which send the standardized Experience API (xAPI) statements. Experience API is an e-learning specification that aims to define a data and communication model to track user activities within learning environments.
- These statements are saved in the Learning Record Store (LRS) and are sent to a real time analysis component updating each player's state of game. Batch analysis uses statements that are stored in the LRS to perform different analysis. Before sending statements to the LRS and real time analysis, the authorization and authentication module is activated.
- Last step is the visualization which performs metrics through dashboards to the stakeholders. Dashboards may also display alerts and warnings and personalized data.
- Eventually, the whole process may take advantage of the gained information and either reassess the game learning design or adapt and

personalize the game for students' needs or to assess students' learning process (Alonso-Fernandez, Calvo, et al., 2017).

Data gathering and analysis which is the key of SGs evaluation may be applied in two feasible ways (Hauge et al., 2014) as shown in Figure 2-11.

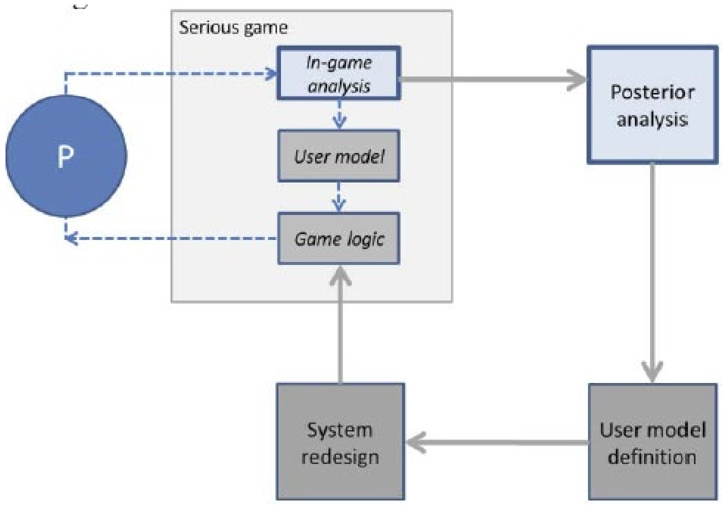

Figure 2-11: In-game analysis and off-line (posterior) analysis (Hauge et al., 2014)

In-game analysis performs individual players' data collection for a better experience sufficiency and a better individual support and personalized learning experience. On the contrary off-line/posterior analysis performs data collection from all the players in order to evaluate and improve the SGs design. In both cases, it is strongly advised to integrate LA into SGs design. In this early stage semantic layers which decode sub-symbolic actions like keystrokes and mouse clicks must be considered in order to interpret these actions into knowledge about educational game design or tasks fulfilled. In order to evaluate educational effectiveness of SGs, they have to be used as an assessment tool where the above behavioral indicators will be matched with predefined learning goals and activities.

Hauge et al., (2014) in their study of LA for SG design performed a LA general framework and a data service which associate LA and SG, the Games and LEarning ANalytics for Educational Research, the GLEANER (Figure 2-12). This framework supports tracking and analyzing in-game players'/learners' behavior.

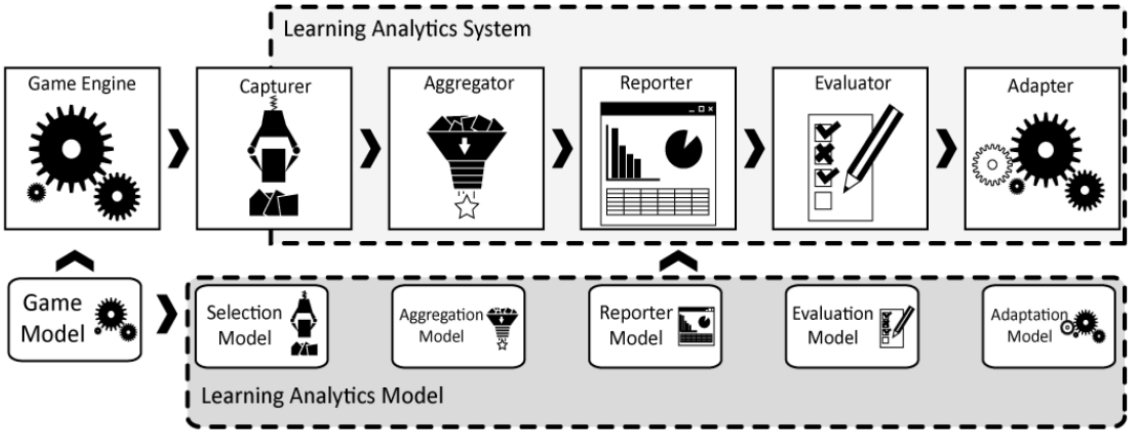

Figure 2-12: Main components of GLEANER (Hauge et al., 2014)

Usually analysis is being performed outside the game in a remote server where the data are being aggregated and analyzed. This implementation includes the following components (Freire et al., 2016).

- *Instrumentation* which is a game-side component where players' games interactions are being stored in order to be sent in batches to a storage server. In this way traffic from small data transmissions will be reduced.
- *Collection and storage* which is a server side component where interaction data are being received, classified, and stored for further analysis.
- *Real-time analytics* are necessary as they allow teachers to intervene during the gameplay session and thus, maximize the learning effectiveness. Usually, these analytics are lightweight and are performed with "time windows" of the last five minutes of players' interaction.
- *Aggregated (batched) analysis*, is a complex analysis of different gameplay sessions and can be executed on the aggregated data from all the gameplay.
- *Key performance indicators (KPIs)*, in educational contexts are quantifiable outcomes like grades, completion or educational effectiveness.
- *Analytics dashboard* is sets of analysis and visualization that are presented in dashboards. These dashboards are configurable for users' needs and can provide a general overview or specific, on demand details.

The GLEANER framework includes the above characteristics. The game triggers the whole process by sending data to a collector. Then the data are being classified and aggregated in order to obtain suitable format to feed the visualization reports with the generated information. Students' assessment may be accomplished in this phase. Finally, the process comes to an end by the adapter which sends back to the game instructions for adapting the game to the player.

Unfortunately, the majority of game development frameworks and engines do not include straightforward support for educational assessment. This makes the developers' task more difficult as it costs time and money for integrating educational features in games. The Realising an Applied Gaming Eco-system, the RAGE project introduced an open source infrastructure that simplifies learning analytics in serious games. RAGE intends to develop, transform and enhance advanced technologies from entertainment games industry into self-enclosed gaming assets that will facilitate game studios for developing SGs in a much easier, faster and affordable way. The Figure 2-13 presents the learning analytics architecture at RAGE project.(Calvo et al., 2016)

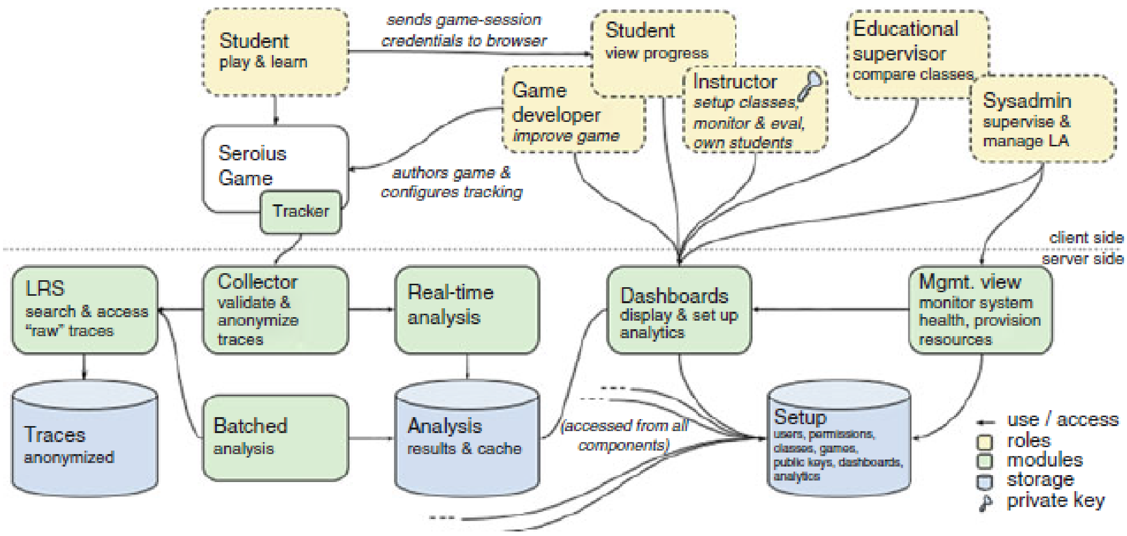

Figure 2-13: Learning Analytics architecture at RAGE project (Calvo et al., 2016)

This architecture consists of mutually dependent components that work in parallel. To perform game learning analytics the following issues must be considered (Freire et al., 2016).

- *Traces collection:* the games' embedded tracker component sends traces to the collector. The collector de-identifies traces but educators may re-identify traces when necessary.
- *Analysis:* analyze the received data to feed analytics queries. The collector disposes the received data to real-time analysis module and to storage for later batched analysis.
- *Visualization report:* authorized stakeholders can access the results and analytics queries either in real-time or batched analysis.

2.5.5.1 Game learning analytics platforms

Game learning analytics may contribute to the improvement of SG development and student assessment. To achieve this, GLA platforms have to be integrated with educational platforms and SG development platforms. Learning Management Systems (LMS) which provide basic information collection are already being used by educational platforms. Game integration with LMSs is still limited with specific LMS combinations (Freire et al., 2016).

Studies for interoperability problems have been made and solutions for integrating SGs in LMSs depending on capabilities and LMS standards have been introduced, for example such as using SCORM or IMS. IMS common cartridge (a specification for educational digital content management) and SCORM (sharable content object reference model) may contribute to standardize to the use of enrich interactions' model that will facilitate the collection of additional analytics data. The proposed model indicates the way for SGs' integration with existing LMSs such as commercial, open source and proprietary by adopting present e-learning standards. However the use of LMSs is restricted to the distribution of the game with limited interaction transferred back to the LMS. In this context, the relief came from the e-learning standards use by reducing the integration complexity problem to the compliance problem with limited set of standards. This approach may contribute to the easier integration scenarios among serious games LA platforms and LA platforms.

According to Freire et al. (2016), the proposed GLA architecture can be integrated as shown in Figure 2-14. Serious game development confronts technical restrictions by the collector component because every analytics platform communicates with the collector by their own proprietary API. However, the Experience API and IMS Caliper which is a standard that enables the collection, storage, and transport of data interactions with learning software and administrative systems, may infer to the standard-based approach of tracking the events inside the serious game.

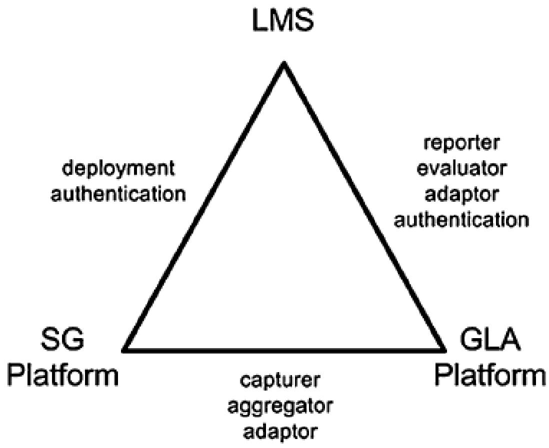

Figure 2-14: Mapping the GLA architecture modules and the integration between platforms (Freire et al., 2016)

xAPI and IMS Caliper data models consist of the following common basic structure:

- *Subject of event:* replies to the answer who generates the event, could be player, tool, and an actor that triggers the event.
- *Action of event:* the action is the gameplay action and interactions within the gameplay.
- *Object of event:* is the target which involved in the interaction.

However more information could be added to this data model as both xAPI and IMS Caliper have adaptive extensible common vocabulary for action and object description. SGs generate interactions data that has different level of detail and events. These different types of events can be described by both xAPI and IMS Caliper.

The collector API in both initiatives can be disconnected from the storage component which allows the replacement of the components and the use of third-party services for analyzing and querying events. SGs platforms can take advantage of a query API for gameplay personalization and adaptation. IMS proposed the IMS learning tools interoperability LTI specification in order to provide third-party external tools directly from LMSs. It aims to facilitate the use of visualization tools within an LMS without having to access the LA platforms. For a similar purpose the SCORM to TLA Roadmap describes four phases for transitioning to a service-based learning platform where TLA represent Training and Learning Architecture.

2.5.5.2 Tracking

As aforementioned in the learning analytics architecture at the RAGE project there are the client's side and the server's side. Authentication and authorization modules are used to achieve connection between server-side components and client's side for secure connection. Other modules are real-time analytics, front-end analytics which refers to analysis configuration and dashboards, and the back-end analytics where data collection and analysis that are sent by the tracker component take place. In Figure 2-15 we can see the RAGE modules that contain the A2 component which allows the connection between different front-end clients and back-end GLEANER applications and the information stored in a LRS.

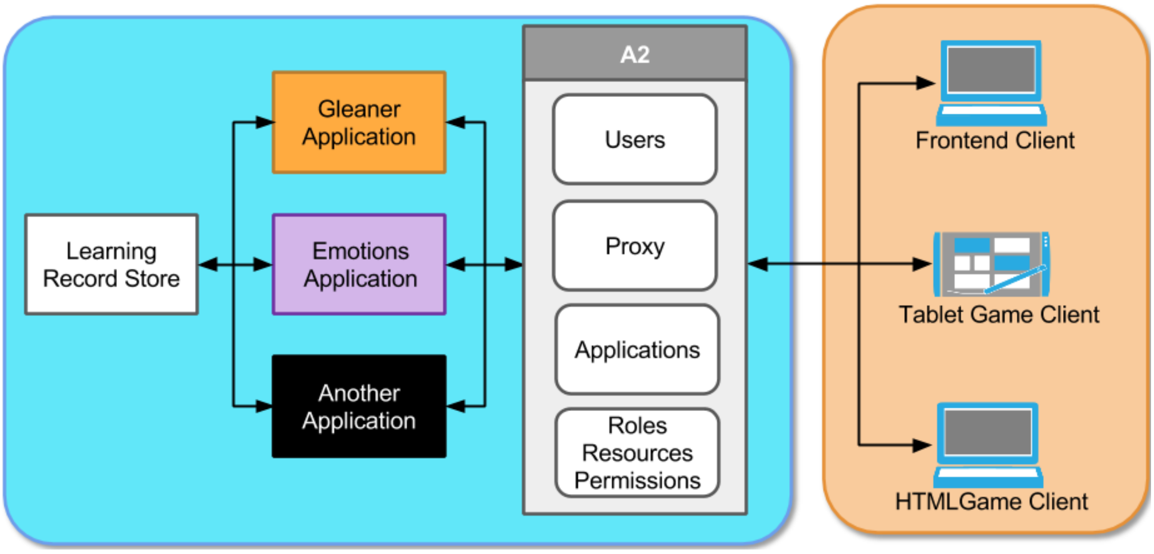

Figure 2-15: RAGE modules include A2 (*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.)

The above RAGE architecture and technologies are shown in detail in Figure 2-16.

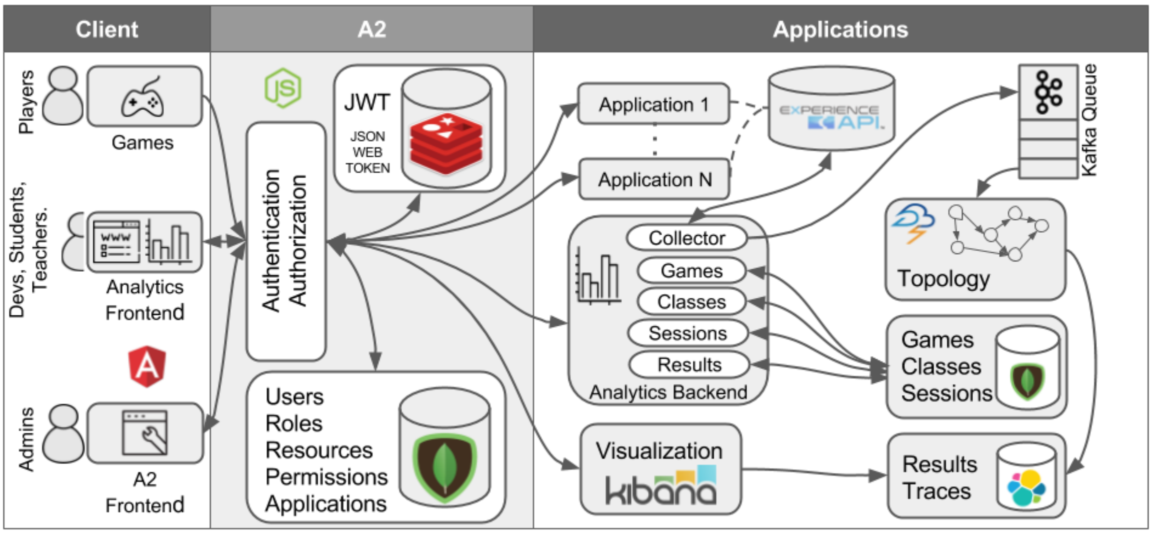

Figure 2-16: Overview of RAGE architecture and technologies (*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.)

The client side includes:

- Players whose interaction traces are sent by the tracker.
- The front-end analytics which provide access to developers, educators and students for different information acquisition disunited by their role.
- The A2 front-end is used by administrators for the management of users' accounts and information.

The A2 component:

- Controls authorization and authentication process of the users and the information sent in traces.
- Contains the JSON Web Token (JWT) which provides the authorization process while user enters the username and password. It returns the user's information token that includes the user's role and is needed for requests to the back-end.
- Manages users, roles, resources, permissions, and applications.

Finally, Applications consist of:

- Experience API, the standard used for data tracking.
- The analytics back-end where information acquired through A2 including game sessions are stored.
- Kafka Queue which saves queues of traces in order to be processed.

- Apache Storm topologies (a topology is a graph of computation which nodes include processing logic and the links between them shows the data flow) which control the analysis process.
- The results that are stored in ElasticSearch (an open source distributed, search and analytics engine).
- Kibana, usually used by teachers and developers, is a data visualization and management tool for ElasticSearch that provides real-time histograms, line graphs, pie charts, and maps. Advanced Applications such as Canvas, may be included which allow custom dynamic infographics based on users' data, and Elastic Maps for visualizing geospatial data.

The tracker component which is on the client's side collects the users' interaction data within the game. The SGs generated traces in the embed tracker component usually sent to an analysis server but may also be stored locally. The tracker must be configured properly in order to start sending traces. As aforementioned the tracker exposes an API design that defines a set of game objects such as completable, accessible, alternative, tracked game object. The tracker may be implemented in technologies as Java, JavaScript, C#, Dot Net and others.

The next step is the authentication and authorization which is included in the A2 component, the user may log in and access server side components. The traces pass the A2 asset and arrive to the collector where they are being stored. The collector expands the traces' xAPI format and adds two identifiers, the gameplay and version identifiers. These identifiers are created at the authentication handshake step using the game tracking code.

Once the traces' data is stored in the collector, it may proceed to real-time analysis component or to LRS component to be stored for later batch analysis. Some reports may be generated from the LRS but not all parts of the xAPI statements can be queried. Aggregated results, related statements, counts of xAPI verbs and others cannot be querying from LRS as it can be implemented over ElasticSearch back-end and some other third party systems. Moreover, querying JSON document structure may differ in syntax.(*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.), (Alonso-Fernandez, Rotaru, et al., 2017)

Tracking system requirements that have to deal with technical issues must be considered. Sufficient bandwidth for online interaction data traces, alternative offline tracking, the server side storage of incoming data which are not only data traces but also user id, game id, session id, user's group and learning activity are some of the issues. The response time of the server has to be minimized and the storage system appropriately optimized for writing loads of data that have to be used. Hence, a NoSQL database like Apache Cassandra, Apache HBase, MongoDB, can be used for writing throughput. Traditional relational database can either be used but clustering and sharing techniques would be necessary. The traces storage system and the analysis system may not be the same (De Gloria, 2014).

2.5.5.3 Real – time analytics

In order to implement real-time analysis the user's interaction data from the collector will be sent in a chain of infrastructure elements. The data may have JSON format with added improvements such as game version and the students' game-plays as students may interact with multiple game-plays. Then, the JSON structure is simplified in its format but retains the key information from the trace containing events, target, type, response, timestamp, and other metadata variables for the analysis. The enriched xAPI statements are sent to the Kafka component and then proceed to Storm analysis.

Apache Strom which is a free open source distributed real-time computation system performs processing on unlimited steams of data. Storm keeps topologies as shown in Figure 2-16, and every storm topology is deployed for analysis and contains processes such as filtering, aggregation, joins, functions, and others.

Storm Flux is a framework and a set of utilities for creating and deploying Apache Storm streaming computations in a much easier way. One of the difficulties is that: the topology graph is written in Java code which requires recompilation and repackaging of the topology jar file in case of any changes. Flux allows the packing of all Storm components in a single jar and the use of an external text file to define the layout and configuration of the topologies.

"*A high-level abstraction for doing real-time computing on top of Storm, called Storm Trident is used to make analysis simpler. Trident has joins, aggregations, grouping, functions, and filters. Moreover, Trident adds primitives in order to have stateful, incremental processing on top of any database or persistence store. Trident has consistent, exactly-once semantics, so it is easy to reason about Trident topologies.*" https://storm.apache.org/releases/current/Trident-tutorial.html

The computation system is deployed through Flux and exports the Flux configuration file (flux.yml) with required information to perform the analysis. A YAML document is created during the configuration step to define topology. The Flux topology defines a topology name, a topology elements list and a DSL (Domain Specific Language) topology specification or a JVM class with the topology definition. The next step is to connect to Kafka and draw data into the system to analyze it.

The storm component as shown in Figure 2-16 receives data from Kafka which is used to reliably maintain a persistent and scalable queue of data. The main concept in Kafka is a topic, which are messages in categories. Processes that publish messages to Kafka may come from different sources and be sent to different processes that subscribe to topics and process the feed of published messages. Kafka obtains data from the collector. The Storm component receives the data proved from Kafka and finally real-time analysis of data may be performed. The eventually analyzed information shall be stored in a database such as MongoDB or proceed to visualization tools.

After the real-time analysis computation, the resulting data are available for visualization components. The format of these data can be specified by the user in the configuration step and usually is in JSON format. The added identifiers in the collector component allow the data to be maintained in game sessions and thus, avoiding the overwriting of the data from different game sessions in case of data storage. This means that new traces are either added or if necessary update the document of game session. Usually, the result information, are stored in ElasticSearch which cooperates perfectly with Kibana visualization tool (*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.).

2.5.5.4 Visualization tools

Graphic visualization of the results is the final part of the serious game learning analytics process. As aforementioned the whole process is triggered by the front-end client, who makes a request for certain information in a particular format which are passed to the required components where real-time analysis is performed and finally the information results are stored in order to be visualized by the visualization component. The analysis output is represented in Figure 2-17.

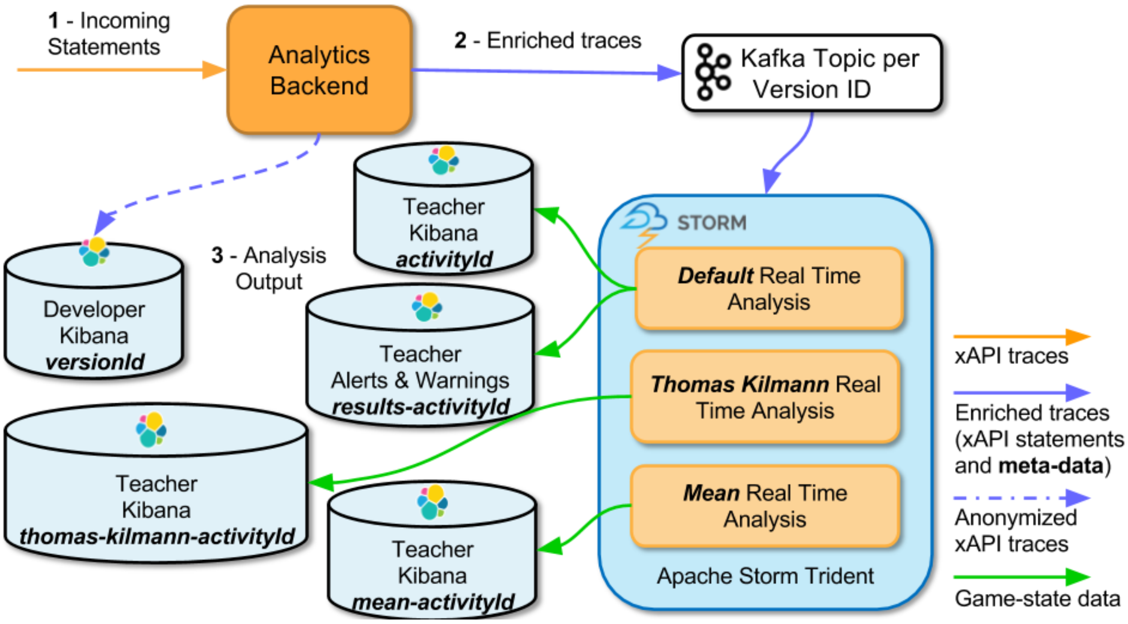

Figure 2-17: A graphic representation of the new Back-end infrastructure (*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.)

The data from different clients in an xAPI Serious Game statement format arrives to the collector. The collector and tracker implementations have already been described. The anonymized xAPI traces are also stored as a list of documents in an ElasticSearch index with versionId (dotted line from Analytics Backend to Developer Kibana versionId). These documents are also in an enriched format but differ in the actor statement as it had to be anonymized in the leading anonymization process. The enriched statements with meta-data information that are received in the Kafka topics comprise the input for the analysis.

The output of the enriched trace is analyzed in order to produce the results. As shown in Figure 2-17 there are different types of analysis, thus, the produced results are different depending on the analysis type. Some of the analysis output is the default, Thomas-kilmann, mean.

The default analysis provides two outputs, one for the Kibana dashboards and aggregated traces for the Alerts and Warnings management. Kibana dashboards have a restriction in order to interpret the data correctly, it requires an ElasticSearch index with a list documents. Alerts and Warnings demand certain conditions to be reached in order to be triggered. Default visualizations for teachers depicts information for their students' performance, progress, participation in games' sessions and instruction videos and many others completables. Default visualizations for developers have different purposes that concern the game design.

Thomas-kilmann output is a certain visualization which requires additional game centered analysis in order to measure and represent responses to different conflict situations exposed in the game. The additional analysis is performed and stored in thomas-kilmann ElasticSearch index. Thomas-kilmann visualizations depict classification of a student's answer, a measure of team productivity, team quality, office morale which is a percentage that shows the degree to which the player's in-game co-workers are happy with the player's choices.

Mean analysis is the analysis that computes the mean of certain attributes of the initial xAPI statements.

The visualizations may be complicated statistics or graphs but it is essential to keep a clear and simple way depending on targeted clients with different knowledge background. There are different tools that can be used for visualization such as OpenLRS Dashboards, OpenDashboard, Kibana and others that request and receive data from real-time components as Kafka and Storm.

OpenLRS is an implementation used by default; all statements from the tracker are stored in LRS. OpenLRS dashboards depict the application of simple analysis on all saved statements regardless the game. The dashboard that is available concerns the number of each xAPI verb was used, the number of statements produced by every user, LRS activity in last week or last year and others (*Rage Analytics Overview · E-Ucm/Rage-Analytics Wiki · GitHub*, n.d.).

OpenDashboard is a web application that provides a framework to display analytics visualizations and data views named cards. This open web source application is developed by Apereo (a network of institutions which support educational software) and OpenLRS (*OpenDashboard*, n.d.). The cards perform a single distinct visualization or data view but use an API and data model. The OpenDashboard aims to serve a flexible and pluggable dashboard framework for open learning analytics environment.

OpenDashboard requires establishing data providers which are sources for data information in order to create sets of preconfigured dashboards for general use. In this point data providers enable new cards to be created in order to access core learning entity from different sources. A card, usually, is a chart or visualization graph. The information included on a card provided from JavaScript Module, an AngularJS Module which feeds the card with basic information and contains card's configuration data. The next step is to create an html file named view.html with the UI markup for the card and add all this information to the main page (*OpenDashboard*, n.d.).

An OpenDashboard uses an open protocol to communicate with a learning management system which makes the integration more complicated and thus, leads not to use it.

On the contrary, Kibana which is an open source analytics and visualization platform and management tool for ElasticSearch has a flexible browser-based interface which allows the creation of dynamic dashboards for visualizing data in a much easier way. Kibana copes with vast amount of data from different sources and performs dashboards that dynamically adjust to changes and display real-time results.

ElasticSearch which is an engine for searching and analyzing a vast amount of data at near real-time is necessary for using Kibana. ElasticSearch cooperate perfectly with Kibana and are in constant development. Data added to ElasticSearch use the syntax of HTTP request and can be queried in the same syntax. The response of ElasticSearch is in HTTP status code and its body is encoded in JSON format. ElasticSearch is made of cluster, node, index, document, shards (subdivision of the index into multiple pieces), replicas (copies of index's shards). The entire document can be stored and its context is indexed for searching inside the document. Documents are stored in JSON format and represent objects. In NoSQL platforms, the standard format for documents is JSON. A document has a type, types exist in indexes, a cluster uses indices to build a lookup indexes which are included in types. These types hold documents with multiple fields. ElasticSearch allows the mapping between indexes fields and types.

In order to import data to ElasticSearch, a Logstash can be used. It is an open source, server-side data processing pipeline that ingests data from different sources concurrently, transform it, and sends it to a stash like ElasticSearch. Logstash supports a variety of inputs in different formats, like JSON, csv, etc. The next step is to access the Logstash configuration file and specify the input, filters, and output. Finally, the data is in ElasticSearch in specified index and type and is ready for the visualization part by using Kibana.

Kibana is a web application and can be accessed through the port 5601, so to access the initial configuration page, all that is needed is to point the browser at the machine where Kibana is running and specify this port number as http://localhost:5601. At least one index pattern must be configured to use Kibana at this first page. This is necessary for the application in order to configure how to access the data as a Kibana index pattern corresponds to ElasticSearch pattern. It is necessary to specify the name of a time field in order to filter the data using global time filter. A timestamp must be correctly mapped to a date field when it is saved in ElasticSearch so as to avoid losing data saved to existing or new index and obtain both results for its use in Kibana. The index that is configured is added to the list of index patterns and thus, all the data and fields associated to its type can be accessed and visualized in Kibana.

When accessing Kibana, the Discover page is loaded by default and allows to inspect the data within default selected indexes and its fields' content. The time filter is set to 15 minutes by default and allows the visualization of data whose timestamp field relates to the established time range. The time filter may be configured. New visualizations may be created based on new or preexisted searches. There are many types of the representation of visualization, tables, charts, metrics, tile maps to associate an aggregation with geographic points. Also, Markdown widgets that are text entry fields in markdown language can be used to enhance visualization. Dashboards may be personalized with multiple data, with added already saved visualization, and dynamic dashboards. Once the visualization of index's data is created, new added data to that index in ElasticSearch will be visible in all dashboards at near real-time because of the connection among Kibana and ElasticSearch. Kibana keeps indexes of created visualization even if we delete them. Moreover, the created visualization can be exported or can be shared by a link, or html code of the visualization can be embedded to another website by simply copying and pasting the code. The link that Kibana generates may contain filters that correspond to queries that can be made to the Kibana web interface. That filters when added directly to the link, allow the creation of different visualization by working on generic visualization.

Kibana is open to different plugins for custom visualization. Although there are several existing plugins for Kibana, users may create their own plugins (*Kibana*, n.d.), (*Elasticsearch*, n.d.).

3 Methodology

In this study, the systematic literature review followed the guidelines proposed by Kitchenham, B. (2004), Procedures for performing systematic reviews. Keele, UK, Keele University, 33, 1–26 (Kitchenham, 2004).

3.1 Planning

According to Kitchenham's methodology, first of all, the need and motivation for this review shall be identified. Thus, all existing information about the research, its current state, the research questions and the selection of studies must be defined. Moreover, the evaluation and definition of a review protocol must be defined.

The review process consists of the following steps:

1) Identification of the research
2) Selection of studies
3) Quality assessment of the studies
4) Data extraction
5) Data synthesis

Finally, discussion and conclusions of the study will be presented.

Figure 3-1 represents the methodology that was followed in the study.

Figure 3-1: Methodology

The main purpose of this research was to review studies conducted on learning analytics in serious game. By reviewing the studies, the issue of serious games as an assessment tool arises. Studies that describe serious games in an educational environment, as well as proposals for the implementation and integration of learning analytics in serious games were the key points for the research.

Although, many studies were found where serious games were used in educational contexts, few presented the methodologies and tools for the implementation and integration of learning analytics in serious game. The majority of the studies concentrate on a theoretical approach of learning analytics in serious games. Studies that present LA in SGs development concentrate on teachers' perspectives, thus, losing their primary purpose of an engaging experience that fascinates students and keeps their retention. In the studies reviewed, we did not find a widely adopted approach to integrate LA in SGs. Moreover, studies that use SGs as assessment tools for student's evaluation and student's acquired knowledge were limited.

According to the goals of this study, the research questions are

- RQ1: Could we identify patterns by applying LA in SGs so as to pre-establish an expert performance baseline and thus predict learning outcomes?
- RQ2: Could commercial games analytics be useful for serious game learning analytics?
- RQ3: Are there defined methodologies for implementing LA in SGs?
- RQ4: Are there any empirical studies for integrating LA in SGs?

3.2 Literature search

In order to obtain studies about LA for SGs the following string was used:

("educational game"* or "serious game"*) and learning analytics*.

The digital libraries and databases where the above query was added were the following: Research Gate, Science Direct, ACM Digital Library, Scopus, Springer, IEEE Xplore, and Academia.

The studies were selected by their titles at this preliminary stage. Then, the selected studies were evaluated based on their abstract and stored. Those that seemed irrelevant were left aside along with duplicate studies.

3.3 Selection of the studies

The inclusion criteria were studies that include Learning Analytics and Serious Games, the use of LA in SGs, the methodologies and tools to apply LA in SGs, potential uses of LA in SGs, Real-time LA in SGs, GLA for educators, and ways to systematize LA in SGs, evaluation of using LA in SGs. Moreover, studies that provide knowledge of Serious Games, Game based learning, and studies that define Learning Analytics were included. The research wasn't restricted by the publication's year as there weren't enough studies published. Most of the studies that were found were published in 2014, and among 2016-2019.

As exclusion criteria the following were adopted:

- Non-English studies
- Studies that were irrelevant

The selection process consisted of two phases. In the initial phase, the collected studies were reviewed by the title, abstract and key words. In the second phase each relevant study was fully studied to evaluate if the study could contribute to the research.

3.4 Quality Assessment of studies

To support data extraction, the studies were analyzed based on the properties shown in Table-1.

Table 3-1: Study analysis properties

General properties
• Author names
• Project name (case study used in paper)
Purpose properties
• Uses of LA in SGs
• LA steps
• Methodologies
• Existing tools for incorporating LA in SGs
• Barriers
• Purpose of study

Once the studies were analyzed, the papers were filtered. Based on the SLR protocol (Kitchenham, 2004) , inclusion and exclusion criteria were used to complete the selection process as shown in Table 2.

Table 3-2: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Studies include methodologies, steps, uses of LA with SG	Studies include commercial game and game analytics
Studies include standards to systematize LA in SGs and simplify educator's effort	Studies include specific games evaluation (e.g. puzzle game)
	Studies presenting LA outside of a game environment

3.5 Data extraction and synthesis

To extract the data, Microsoft Office Excel was used. Table 3-3 represents the properties that guided this review.

Table 3-3: Properties of reviewed studies

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
1	Alessandro De Gloria	Games and Learning Alliance (Learning Analytics and Educational Games: Lessons Learned from Practical Experience)	2013	improvement of assessment of experimental research on educational game-based instruction, adaptive and personalized learning	Questionnaire for external analysis of learning process, Data collection, data storage, data analysis	LA system was used to track interaction, pre-test & post-test measurment, GLEANER	GLEANER	no Internet access or insufficient bandwidth	LA aims to harness the power of big data and data-mining techniques to improve the assessment of the learning processes	The Big Party, Lost in Space, La Dama Boba, Donations,
2	Alessandro De Gloria, Francesco Bellotti, Riccardo Berta	Serious Games for education and training	2014	provide detailed information of player's performance, immediate intervention, assessment, adaptivity, personalization	consider a complex mix of disciplines and technologies as AI, HCI, networking, computer graphics and architecture, signal processing, web-distributed computing, neurosciences.	combine advanced technologies, educational and entertainment goals	eAdventure platform, http://creatools.gameclassification.com/, GenGSG framework, LM-GM model	evaluation methods are still under-developed	assessment, feedback, improve game design	CancerSpace game, Real Lives 2010, SimVenture
3	Ana R. Cano, Baltasar Fernández-Manjón, Álvaro J. García-Tejedor	Downtown, A Subway Adventure: Using Learning Analytics to Improve the Development of a Learning Game for People with Intellectual Disabilities	2016	players engagement, the effectiveness of the game design and the validity of the user requirements	LA module inside game to acquire data in real time, relevant learning in-game users' data	GLA model	integrate a LA module in the game	wide range of cognitive conditions hinders standardization of the process followed in this development	game aims to improve the learning process of the intellectual impaired population in the process of being self-sufficient	Downtown: A Subway Adventure, is teaching young users with intellectual disabilities how to use the subway by themselves
4	Ángel Serrano-Laguna, Baltasar Fernández-Manjón	Applying learning analytics to simplify serious games deployment in the classroom	2014	To improve the educational process, LA results and metrics can benefit teachers, organizations and students themselves	to collect, structure, analyse and represent /visualize. Define precisely the educational goal, establish a reliable connection between game interactions and educational goals, design clear visualizations	keep track of the students through connected device, so the device can communicate back the resolution process; a LA system must listen to this user data, analyze it and present it to the teacher	game designer/programmer decides how the data are transmitted to the teacher, teacher and designer have to define which concrete interactions prove that a student accomplished a goal, 2 modes : In-game assessment, External analysis	QWERTY keyboard and LCD screen - One of the disadvantages of this type of systems is that the interaction students perform is limited, since in most cases answers consist of selecting an option or writing a word. Thus, both data for analysis and results' visualizations are also limited	simplify teachers' task when using games by providing real-time information of the actual students' use of the games while in the classroom. This approach is specially focused on delivering assessment data to the teachers	Lost in Space <XML> game
5	Antonio Calvo, Dan C. Rotaru, Manuel Freire, Baltasar Fernandez-Manjon	Tools and Approaches for Simplifying Serious Games Development in Educational Settings	2016	Evaluation profiles, Adaptation profiles. An adaptation profile execution may change the content of the game scene.	techniques (assessment, tracking and other classroom management features) applied at the design stages of the SG.	the game requirements, platforms, desired interactions and mechanics, game genre, learning objectives, time constraints, and resources and supported technologies.	The learning analytics asset provides a tracker client available in different programming languages, including JavaScript, Java and C#, which can be integrated with other frameworks and game engines such as libGDX and Unity.	To generalize the use of games in formal education settings, educators need additional support. Small budgets for SGs, maintain high player engagement. Learning assessment support increase cost. Collected data privacy policy. Lack of tools to easily integrate games with LA for learning outcomes evaluation. Technical characteristics are frequently neglected	n/a	n/a
6	C. Alonso-Fernandez, A. Calvo, M. Freire, I. Martinez-Ortiz, B. Fernandez-Manjon	Systematizing game learning analytics for serious games	2017	understanding or improving the learning process, Students' assessment, Learning Plan-Educational Goal, Personalized and adaptive gameplays, SG' improvement	learning and game design determine what should be tracked, generic Tracker component sends the standardized xAPI statements, statements are saved in LRS, personalized dashboards, configured alerts and warnings are displayed	adding a tracker to the SG that sends player interaction data(traces) to a server	GLA system	lack of widely adopted standards to communicate trace data from games to tracking module. Each SG ends up being tied to its own LA solution. Updates in the LA means development cost and reduce GLA use. Privacy laws and regulations, Anonymization, Reuse of data produced by experiments	systematizig GLA fo SG	n/a

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
7	Callaghan, McShane, Gomez Eguiluz	Using Game Analytics to Measure Student Engagement/Retantion for Engineering Education	2014	measure standard metrics, determine user retention,	define actionable data in game design stage, track, analyze and visualize	core & custom analytics	Game Analytics was used	n/a	Integration of analytics into the game to measure student retention	Circuit Wart
8	Cariaga, Feria	Learning Analytics through a Digital Game-Based Learning Environment		describe potentials, patterns and actions, improve learning & game design	collect (select, capture), aggregate, analyze, visualize data	define Who, What, Why, How, modify game flow according to LA Framework,capture additional data, process and analyze and present analysis in Game Center	LMS, intergrating learning mechanics framework in game mechanics	data privacy and ethics	present LA framework for GBL to improve learning actions through visualization & processing of data.	Kinespell
9	Carolyn McGregor, Brendan Bonnis	Big Data Analytics for Resilience Assessment and Development in Tactical Training	2016	enable the trainer to personalize the resilience development of the individual in the activity and to focus on the areas of need and necessity. It also provides a repeatable tool for testing scenarios and evaluating individuals across the same scenarios.	A)Determine the number of participants and their role. B)Define the Stressors. C)Link Stressors to Game Function. D)Define Analytics for Stressors	utilizes the Athena Platform	n/a	n/a	n/a	n/a
10	Chanachai Siriphunwaraphon, Nattapong Tongtep, Thatsanee Charoenporn	Human Personality toward Digital Gameplay Analytics for Edutainment-based Instructional Design	2016	selecting or designing learning material in consonance with learners preferences, predict the preferable games and preferable learning material determinately	Survey Design - Data Collection - Data Pre-processing - Feature Extraction - Learning Model Construction - Learning Model Construction	n/a	n/a	n/a	n/a	n/a
11	Christian Sebastian Loh, Yanyan Sheng	Serious Games Analytics Methodologies for Performance Measurement, Assessment, and Improvement	2015	improve skill and performance, obtain insights for learning and game design improvement, measure game effectiveness, behavioral profiling	data collection and analysis, information visualization	game telemetry, analyse log data, clustering techniques	software telemetry, Information trail framework	high production cost	measure in-game performance	Save Patch game, iSTART-2, Alien Rescue, Implulse
12	Christian Sebastian, I-Hung Li	Using Players' Gameplay Action-Decision Profiles to Prescribe Training	2016	performance measurement, assessment, improvement, profiling, "prescription" for training	using telemetry for traces, visualization through heat-mapping using similarity measures.	telemetric methods, similarity measures	Serious games with in-built capabilities for telemetry and analytics		reduce training cost	in-house serious-Unity3D game engine, onelevel Maze with a single Escape portal located in a room.
13	David Gañán, Santi Caballé, Robert Clarisó, Jordi Conesa	Analysis and Design of an eLearning Platform Featuring Learning Analytics and Gamification	2016	assessment and automatic feedback to students, instructors: predicting performance, modeling profiles for customization of student needs, goals and individual skills	data visualization techniques, process of collection and analysis, e-assessment tools	eLearning tools, use of standards, intelligence (BI) system	i) The IEEE Standard for Learning, data model for tracking traces, LMS to query collected information ii) xAPI	lack of a common data model for representing student interactions: each system uses its own model, which hinders the construction of a LA model that manages information from different sources	n/a	n/a
14	EDUCAUSE	7 THINGS YOU SHOULD KNOW ABOUT Analytics	2010	monitor the progress of >500 students, discern patterns,trends, and exceptions, construct predictive models, improve student achievement, retention, and graduation rates, assessment	compile, analyse tracking information, collect and store data in LMS, visualizations,	real-time information	LMS, tools and LMS plug-ins that are designed specifically to generate meaningful analytics.	legal and ethical considerations, including privacy, security, and ownership, misclassifications and misleading patterns	make more informed decisions, targeted ads, develop student recruitment policies	n/a

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
15	Erik Harpstead, Christopher J. MacLellan, Vincent Aleven, Brad A. Myers	Using Extracted Features to Inform Alignment-Driven Design Ideas in an Educational Game	2014	assess the game design and compare alternatives, redesigns, understanding players' behavior, students' feedback as guidance, find patterns	pre- and post-tests to measure learning , PRM metrics, data collection and evaluation, define structural patterns, compare metrics	clustering method, EDGE framework	analysis of principle-relevant metrics	it is difficult to design educational experience, educational experience can be misaligned with its educational goals, inconsistent feedback	evaluate the alignment of educational game against its goals	RumbleBlocks game
16	Helene Fournier, Rita Kop	The value of learning analytics to networked learning on a personal learning environment	2011	general, not specifically for SGs, improve students learning experience. Increase effectiveness of learning	general, not specifically for SGs	general, not specifically for SGs	LMSs,MOOC	general, not specifically for SGs	general, not specifically for SGs	n/a
17	Heraclito A. Pereira Jr.1, Alberto F. De Souza1 and Crediné S. De Menezes	A Computational Architecture for Learning Analytics in Game-based Learning	2016	assessment of GBL, obtain patterns, improve learning & game design	collect, analyze, visualise	relational analysis and data mining techniques, separate assessment engine from game engine, telemetry	GTML-game trace marked language, WEKA- mining software, artificial neural network	lack of consolidated & easy to use resources to assess GBL and learning evaluation implementation difficulties	propose a computational architecture for LA in GBL	n/a
18	https://apereo-learning-analytics-initiative.github.io/OpenDashboard/	OpenDashboard	201 9	n/a	n/a	n/a	framework to display visualization	n/a	n/a	n/a
19	https://books.google.gr/books?hl=el&lr=&id=m5A-DwAAQBAJ&oi=fnd&pg=PA73&dq=tracker+component+Serious+Games&ots=6SUazLJUUU&sig=bnui2uOs5cwu1O5_zHt7SznHvTU&redir_esc=y#v=onepage&q=tracker%20component%20Serious%20Games&f=false	Serious Games: Third Joint International Conference, JCSG 2017, Valencia ... - Βιβλία Google; Full Lifecycle Architecture for Serious Games: Integrating Game Learning Analytics and a Game Authoring Tool	201 7	to benefit from feedback, to evaluate players, analyze game level and learning level, real time information for teachers	data tracking, data analysis, results visualization	architecture that include interaction tracker and analytics platform, xAPI-SG interaction model to standardize trace collection, default set of analysis and visualization	xAPI-SG, open source visualization engine Kibana connected with Elasticsearch, embedded tracker, collector, LRS	n/a	to generate actionable feedback, to integrate GLA into development platform	EU H2020 SG-related project
20	https://github.com/e-ucm/rage-analytics/wiki/Rage-analytics-Overview	Rage analytics Overview · e-ucm/rage-analytics Wiki · GitHub	2019	results and analytics queries either in real-time or batched analysis	Traces collection, analysis, visualization	RAGE architecture	an open source infrastructure that simplifies learning analytics in serious games	n/a	intends to develop, transform and enhance advanced technologies from entertainment games industry into self-enclosed gaming assets that will facilitate game studios for developing SGs in a much easier, faster and affordable way	RAGE project
21	https://www.elastic.co/elasticsearch	Elasticsearch: The Official Distributed Search & Analytics Engine | Elastic	2019	n/a	n/a	n/a	ElasticSearch is an open source distributed, search and analytics engine where results are stored	n/a	n/a	n/a

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
22	https://www.elastic.co/kibana	Kibana: Explore, Visualize, Discover Data | Elastic	2019	visualize data, learners progress, game design improvement	Tracking, aggregating, LRS, real-time analysis	tracker , front-end & back-end analytics	RAGE module	n/a	n/a	n/a
23	I. Perez-Colado, C. Alonso-Fernandez, M. Freire, I. Martinez-Ortiz, B. Fernandez-Manjon	Game Learning Analytics is not informagic!	2018	real-time analytics allow teachers to maintain awareness of student actions in-game, asynchronously analytics evaluate students and what was learnt	Learning goals (Learning Design) - Game goals (Game Design) - Traces to be sent (by game) - Analysis model (Game-dependent analysis) - Visualizations (Game-dependent visualizations)	Traces - xAPI - SG Model (xAPI standard = statements composed of three main fields: an actor, a verb and an object)	LAM-provides the models on how information should be tracked, aggregated and reported to a LA System (LAS)-(WHAT, WHY, HOW, WHO). Meta-LAM for multi-scale games	multiple games-difficult to measure how much of the game remains to be completed,describe the larger game as a whole. Systematizing LAMs for multi-scale games, there are no standard or widely accepted model on the literature that covers this issue	the most valuable educational insight is obtained from analyses that take into account both the learning goals and how those learning goals are related to the game goals; and this is simply not possible for the default LAM, which must necessarily be generic	n/a
24	Jannicke Baalsrud Hauge, Matthias Kalverkamp,Francesco Bellotti, Riccardo Berta, Alessandro De Gloria, Giulio Barabino	Requirements on learning analytics for facilitated and non facilitated games	2014	analyse, evaluate and construct new knowledge based on the in-built feedback	n/a	n/a	Kolb's learning cycle and Nonaka's SECI model, a set of indicators that give immediate feedback to the players	debriefing outside the game, LA based on observation and indicators of game, the lack of LA tools within the games requires an experienced facilitator and small classes of max 18 participants	to investigate if the game can be used in a non-facilitated or facilitated way, analyse and evaluate their actions and the impact of these actions	The game, SHORTFALL, raises awareness of environmental impact of decisions taken in the supply chain and includes a set of indicators that give immediate feedback to the players
25	Jannicke, Baltasar	Implication of LA for SG design	2014	understanding and optimizing learning and the environments in which it occurs, Improve the assessment of progress, performance, learning outcomes, game quality and user appreciation	In-game analysis and off-line (posterior) analysis. Link the educational goals of the game with the in-game observable data and to support their collection.	an aggregator (the next step of GLEANER model) was built to generate a joint status history file: typically a time-ordered relational database of events and associated objects, attributes, parameters and values.	GLEANER-Games and LEarning ANalytics for Educational Research, LAM, LAS, API	difficulties on measuring learning outcomes achieved through SGs' use. In many aspects the process of gaming may conflict with the process of learning. Many games analyse player data, but fail to analyse the learning.	n/a	n/a
26	Johannes Breuer, Gary Bente	Why so serious? On the relation of serious games and learning	2010	n/a	n/a	n/a	n/a	n/a	asses final outcomes, monitoring training process without impairing learning experiences	n/a
27	Malliarakis, Satratzemi, Xinogalos	Integrating learning analytics in an educational MMORPG for computer programming	2014	monitor/assess individual performance, evaluate the game,	(capture, report, predict, act , refine) collect, analyze, visualize	a Framework with 6 axes, activity metrics, session time/last access, assessment methods, errors, collaboration metrics, engagement & performance metrics	mathematical model that automate the process of gathering results & drawing conclusions with the help of LA	lack of framework to use properly LA in games, games used in education don't allow assessment functionality.	propose a framework for integrating LA mechanisms in MMORPG	CMX game
28	Manuel Freire, Ángel Serrano-Laguna, Borja Manero, Ivan Martinez-Ortiz	Game Learning Analytics: Learning Analytics for Serious Games	2017	student misconceptions and progress., game development, customer metrics, community metrics,game metrics,Real-time gathering, analysis and presentation, users' behavior, reveal patterns, and GLA for game design and game testing	Basic Principles of GLA implementation : Instrumentation, Real-time analytics, Aggregated (batched) analysis, Key performance indicators (KPI), Analytics Dashboard	Data-driven analysis of user interaction. IMS Common Cartridge and SCORM to standardize progress reporting, collect additional analytics-oriented interactions, with a higher levels of abstraction in LMS	LMS,CMS, ADAGE, a click-stream (telemetry) data framework that looks inside the data stream of educational games. The ADL Experience API (or xAPI) (Advanced Distributed Learning, 2013) and IMS Caliper (IMS Global Consortium, 2015a)	some teachers are reluctant to use what they call "machine evaluation", mainly because they do not fully understand the underlying technology. In automated evaluation teachers have the final say, and who will bear the responsibility for errors.	A free, open-source, fully-fledged GLA infrastructure that can be deployed by serious game developers and institutions to analyze and learn from their games and players.	Game-specific analytics. European project RAGE , a new software architecture that simplifies LA in SGs. New business models enabled by pairing serious games with learning analytics-Serious Games as a Service.

29	A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case s
30	Matthew C. Gombolay, Reed Jensen, Sung-Hyun Son	Machine Learning Techniques for Analyzing Training Behavior in Serious Gaming	2017	performance prediction, which training objectives are reflected in actual play , identify player's disengagement, personalized lesson plan	n/a	machine learning techniques, studying cluster to identify players' type	n/a	n/a	understand player behaviour rather than performance	Strike Group Defender	
31	Meihua Qian, Karen R. Clark	Game-based Learning and 21st century skills: A review of recent research	2016	provide timely feedback	collect data	n/a	n/a	n/a	n/a	n/a	
32	Miroslav Minović, Miloš Milovanović	Real-time Learning Analytics in Educational games	2013	track and evaluate students learning progress, real-time analysis, improve learning and motivation	collect traces, discover patterns, visualize student knowledge	data mining methods, cluster analysis of logs to discover learning patterns, visualize student- overlapping model	GRAPPLE Visualization Infrastructure Service, LMS (PIM & PSM platform)	n/a	player goals and game progress, motivating students	2D adventure educational game session	
33	Mohammad Ali, Swakkhar Shatabda, Mubasshir Ahmed	Impact of Learning Analytics on Product Marketing with Serious Games in Bangladesh	2017	reduce typical marketing cost and time, delivers commercial messages through games, give promotional offer, get feedbacks or any marketing outcomes from SGs, to predict users choice on any particular consumer product.	collection of in-game raw data, application of LA method, identify players personal choices, behaviors and performance. Use personal behavioral data to take decisions in different fields	interactions analysis and visualization. Game Engine-Data Generate-Capture Related Data-Aggregate-Report.	LA method collect players' data, store them into game database, analyze data to get a specific result based on our learning goal. Specific tool is not mentioned	illegal, player don't know the purpose of the game	advergaming - take inferior time and is less expensive than traditional marketing method	"Grab the Drink" / register with their name, student id, age, and gender before playing the game	
34	Morata, Fernandez, Freire, Martinez-Ortiz, Fernandez-Manjon	Game Learning Analytics for Educators	2019	provide insight into in-game student action, evaluate, validate and improve games, students evaluation,	interaction data collection, analyse data, visualization,	pre/post questionnaire/tests, prediction models, compare models as an assessment method	xAPI-SG	LA for SGs is still fragile, privacy and security issues	simplify educators' application of SGs in class	n/a	
35	Ninaus Manuel, Kober Silvia E., Friedrich Elisabeth V.C., Neuper Christa,Woo d Guilherme	The potential use of neurophysiological signals for learning analytics	2014	neurophysiological signals could inform serious games about the progress of the learner	Behavioral pre-testing , identify suitable rules for learning, using neurophysiological methods, monitoring brain activation to identify learning analytics frameworks	Using neurophysiological data for monitoring brain activity in serious games	Near-infrared spectroscopy (NIRS) is a non-invasive optical neuroimaging technique that find functional activation of the human cerebral cortex	n/a	to use acquired information/metric in complex gamebased learning tasks in a SG. Use result in LA frameworks based on to assess and optimize learning	The game "U get it U catch it". (http://studies.seriousgamessociety.org/). An embedded algorithm based on neurophysiological signals in a LA framework can identify different cognitive processes during gaming/learning.	
36	Perez-Colado, Cristian Rotaru, Freire, Martinez-Ortiz, Baltasar Fernandez	Learning analytics for location-based serious games	2018	game improvement, assessment, real-time analytics	collect, analyze and stored data, define additional game-specific inputs, create additional analysis, location-Based visualizations - default heat-map visualization	LA infrastructure: client-side, server-side, xAPI specification, statements composed of triplets of noun, verb, and object, generic & custom analyses	proposed xAPI extension, GLM, GeoJSON, customized analysis algorithms, data model design	Lack of standardized method for communicating player interaction data	propose method that uses xAPI standards to support location-based SGs	game that guided players through different sports-related facilities within a large outdoor area	

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
37	Popescu, Romero, Usart	Serious Games for Serious Learning Using SG for Business, Management and Defence Education	2013	students assessment, self-assessment, game effectiveness	pre/post test surveys, feedback questionnaire	n/a	n/a	teachers reluctance on using SGs	Integrate SGs into curriculum	MetaVals game
38	Sara de Freitas, Fotis Liarokapis	Serious Games: A New Paradigm for Education?	2011	game-based assessment, personalized information, scaffold the processes of learning	learning-instruction-assessment, define learning objectives, clear player goals, learning content, debriefing, system feedback	data collection, learner profiling and modelling in all design phases	n/a	n/a	test-bed environment for testing conceptual and pedagogically driven design experiments	Roma Nova game with dialog environments
39	Serrano-Lagunaa, Martínez-Ortiza, Haagb, Reganb, Johnsonb, Fernández-Manjón	Applying standards to systematize learning analytics in serious games	2016	students assessment, real - time learning problem identification, behavior and performance analysis	data interaction tracking, collection	telemetry, compare game & learning goals, interaction model	event-based tracking, completables, alternatives, meaningful variables, custom interactions, SCORM, PSLC DtaShop, CAM, xAPI, IMS Caliper, LRS	lack of tools to make available for analysis the captured data	Standardization for supporting infrastructure to decrease the LA applying cost	Countrix SG that implements the SGs xAPI profile and is connected to LA framework
40	Serrano-Lagunaa, Torrentea, Moreno-Gera, Fernández-Manjóna	Tracing a little for big Improvements: Application of Learning Analytics and Videogames for Student Assessment	2012	assessment, understatding learning process	tracking interaction data, analyze data, combine different type of traces, data visualization	traces logged, automatic assessment, evaluate game states relevant information of in-game play	built-in tracking system, external analyzer	n/a	assess and evaluate students' progress and debug the game design	n/a
41	Shoukry, Göbel, Steinmetz	Learning Analytics and Serious Games: Trends and Considerations	2014	improve learning, real-time insight, identify user attributes, strengths and weaknesses, patterns recognition	capturing, tracking, aggregating, analyzing, visualizing learners interaction data	CbKST model, a Competency, an Evidence, a Task/Action models, NGLOB framework, cluster analysis	OLM (visualization), Replayer, Zoodles	n/a	analytics-efficient design	only mentioned
42	Theofylaktos Anastasiadis, Georgios Lampropoulos, Kerstin Siakas	Digital Game-based Learning and Serious Games in Education	2018	n/a	n/a	n/a	n/a	n/a	Utilize SGs as educational tool to improve soft skills and enhance student's learning procedure	n/a
43	Tlili, Essalmi, Jemni, Kinshuk	An Educational game for teaching computer Architecture: Evaluation using learning analytics		evaluate learners and game efficiency, efficiently use in-game interaction data, feedback, learners' support prediction, plan interventions, improve lesson design and game learning environment, enhance learners' knowledge , personalization	collect traces, send to external database, analyze, visualize data	Analyze data by classification, regression, clustering, summarization, dependency modelling, deviation detection.	pre and post-tests, SPSS	n/a	to make CAG more efficient, interactive and fun	Computer Architecture Game CAG
44	W.Westera, R.J. Nadolski, H.G.K. Hummel, I.G.J.H.Wopereis	Serious games for higher education: a framework for reducing design complexity	2008	assess progress, provide feedback and make intervention	create predefined interview, evaluate interview, tracking, evaluating, provide feedback	Emergo methodology toolkit, ADDIE-based methodology, tests	IMS Learning Design technology specification, (Location, object, role, scenario builder)	complex, time consuming and costly development of SGs	reduce the design complexity at conceptual, technical and practical level and provide framework	n/a

A/A	Author(s)	Title	Year	Uses of LA in SGs	LA steps	Methodologies	Existing tools for incorporating LA in SGs	Barriers	purpose	case study
45	Wim Westera, Rob Nadolski, and Hans Hummel	Learning Analytics in Serious Gaming: Uncovering the Hidden Treasury of Game Log Files	2013	improve learning outcomes, develop and apply predictive models in instructional system, retention rates, automated assessment	logging system, logging aggregator, logging files, statistics from data, metrics from pre-test prior knowledge	tracking function of interaction data, profile data, access statistics and test results	LMS as Moodle and Blackboard, EMERGO game engine	the actual use of logging data is quite limited, the assessment of learning progress is based on closures and performance milestones, the process of gaming counteract the process of learning , continuous feedback may demotivate learners	explore to what extent the logging data of the used games would reveal meaningful patterns, variables and relationships	5 games linked together in a single game run (1. Wadden Sea, 2. Wind energy, 3. Lake Naarden, 4. Micro pollution, 5. River management(1. Wadden Sea, 2. Wind energy, 3. Lake Naarden, 4. Micro pollution, 5. River management).
46	Wim Westera, Rob Nadolski, and Hans Hummel	Serious Gaming Analytics: What Students´ Log Files Tell Us about Gaming and Learning	2014	find meaningful patterns and relationships, improve teaching and learning, tracing bottlenecks, personalised learning, game evaluation & improvement, assessment	extract logging data, combine with user profile data, explore and correlate key data, logging analysis(in-game & posterior), data collection, processing & results	link observed behavioural patterns with the effectiveness of learning , component-based architecture	LMS(Moodle,Blackboard), eLAT: exploratory LA Toolbox	lack of established methods and tools for linking logging data directly to a game play, continuous feedback may dissempower and demotivate learners, privacy protection and legal issues	identify relevant player bahaviours and performance patterns, achieving better match between gaming & pedagogy	VIBOA environmental policy game
47	Yaëlle Chaudy, Thomas M. Connolly, Thomas Hainey	EngAGe: A link between Educational Games Developers and Educators	2014	customise the assessment to teacher's needs. Identifying improvements with LA. Making the changes to the assessment system with a visual language.	Definition of the assessment is specified in a single configuration file (formatted in DSL), independent from the game. DSL has its own semantics and syntactic rules. A set of Web Services: Performing the Assessment*	data collection, data mining	EngAGe engine for Assessment in Games used as a link between developers and educators. EngAGe allows the separation of the SG's game mechanics and its assessment logic, making the whole system more flexible.	Developing a game's assessment is a very complex and multidisciplinary process, requires both technical and educational knowledge. SGs are too often distributed as "Black boxes", which means they are closed and self-contained systems	allows developers to save a considerable amount of time and cost, not only implementing the assessment process into their game, but also thinking it through.	n/a
48	Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón,	A methodology for assessing the effectiveness of serious games and for inferring player learning outcomes	2017	assess SGs' effectiveness, infer/measure learning outcomes, discover point for game design improvement	design phase (transfprm learning into game mechanics and learning outcomes), non-disruptive in-game tracking, store and analyze interactions, compare FA & IA	created game design pattern (included strategy, practice, mastery), calculate learning outcomes from practice and mastery phase, assessment in 2 phases (assessment threshholds), analysis of observables & signals	custom embeded tracker component, collector server, python scripts to query database	lack of SGs effectiveness assessment methods, design flaws (of game or FA & IA formulas)	methodology to structure design and assessment of SGs for infering learning outcomes and asess SGs effectiveness as educational tool	The Foolish Lady SG
49	Perez-Colado, I. J., Perez-Colado, V. M., Martínez-Ortiz, I., Freire-Moran, M., & Fernández-Manjón	uAdventure: The eAdventure reboot Combining the experience of commercial gaming tools and tailored educational tools	2017	students' assessment, game evaluation, automate insights of learners' gameplay	link game states that are associated with educational learning goal or with in-game players' skills, data collection, analysis, and visualization	uA framework, big data & analytics techniques	uA platform, uA editor & interpreter',xAPI tracker component, LRS	n/a	uAdventure authoring tool to simplify SGs development, improve lifecycle & reduce authoring and maintenance cost	n/a
50	Alonso-Fernández, C., Cano, A. R., Calvo-Morata, A., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2019)	Lessons learned applying learning analytics to assess serious games	2019	insigt of learning progress, learning assessment, game effectiveness, improvement/validation of the SGs development, feedback	trace interaction data, analyze, visualize, evaluate	define clear goals, link learning goals and game design, trace, collect, analyze, visualize, evaluate the process	follow LAM model, xAPI-SG Profile, analytics platform	n/a	to prove that GLA can be used for different purpose, design improvement, the process of evaluation and deployment	Conectado, DownTown, First Aid Game.

4 Results

The initial search with the query “("educational game"* or "serious game"*) and learning analytics*” returned 318 papers and 7 (Springer) books. In the preliminary phase 118 studies were considered potentially relevant based on their and abstract. These studies were evaluated after the application of inclusion and exclusion criteria and the duplicates were removed. Finally, 40 studies and 10 chapters from 4 books were selected for quality assessment. Figure 4-1 shows the process.

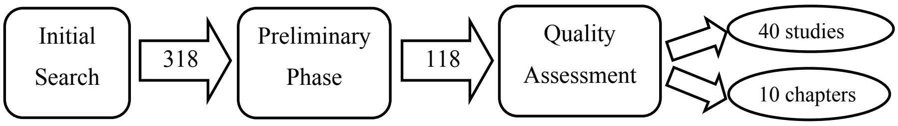

Figure 4-1: Process flow.

4.1 Quantitative analysis

Figure 4-2 shows publications related to the study over the years. Most of the publications were found in years 2014 and 2019.

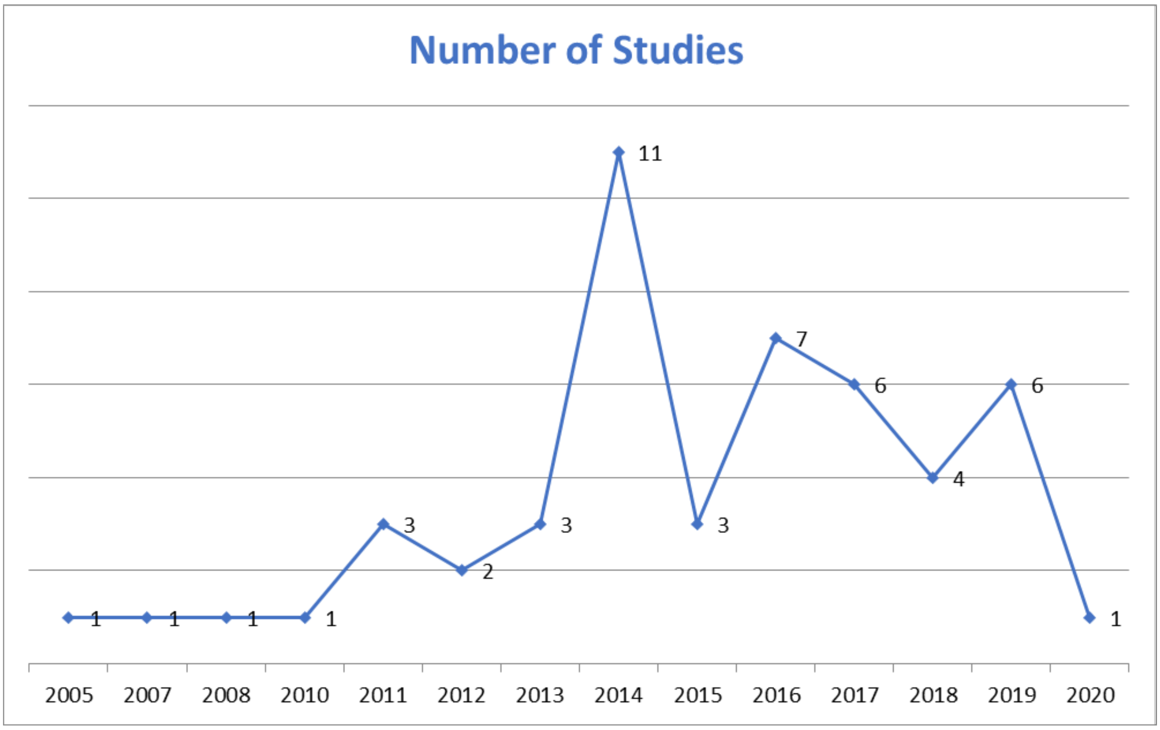

Figure 4-2: Number of studies per year.

The studied publications were classified by their type, as shown on Figure 4-3. Most of the publications were conference papers (20), the rest were mostly journal article (16), several were book chapters (10), and 4 were web pages.

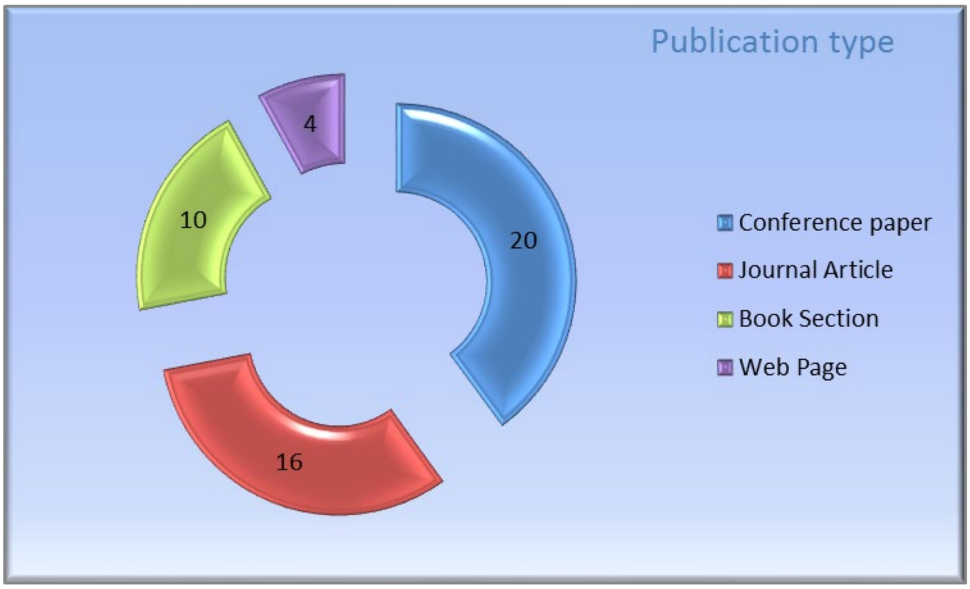

Figure 4-3: Distribution of studies by type

An additional classification of the papers was the theoretical and practical approach of learning analytics in serious games. Half the studies (51%) follow a theoretical approach and half (49%) presented a practical approach.

4.2 Qualitative analysis

In this section, a qualitative analysis will be applied to the selected studies in order to discuss and answer the research questions.

4.2.1 RQ1: Could we identify patterns by applying LA in SGs so as to pre-establish an expert performance baseline and thus predict learning outcomes?

Many reviewed studies refer to patterns identification and how the learning process may take advantage of identified patterns.

In the book chapter "A Meta-Analysis of Data Collection in Serious Games Research" by Smith, S. P., Blackmore, K., & Nesbitt, K., Loh et al., (2015a), authors reviewed SGs data collection techniques and investigated issues as what, when, how, where and why data is being collected. Useful patterns may be identified with the help of visualization and data mining techniques or with the robust combination of two. The importance of collected data quality and validity affect the validity of the identified patterns. The scope of SGs data collection derives from various reasons, such as measuring changes in knowledge, skills, behavior, attitudes or individuals progress changes or organizational, thus, the suggested standardized data collection techniques enables comparing and contrasting outcomes.

In the book chapter "Guidelines for the Design and Implementation of Game Telemetry of SGs Analytics" by Chung, G. K., Loh et al., (2015a), players' behavioral patterns are identified by means of game telemetry with cluster analysis techniques. However, it is necessary to consider two factors when designing measures of in-game strategies that are "*(a) What sets or sequences of in-game behaviors might reflect productive and unproductive use of cognitive demand X? (b) What sets or sequences of in-game behaviors might reflect common errors in the domain?"* (Chung, G. K., Loh et al., 2015a; p. 73). It is outlined that the identified patterns shall be compared to the task and to the player's expected knowledge of the area. As measures show, the players' behavioral patterns that have been discovered shall depict the desired knowledge and skills for those patterns to be delicate to dissimilarity in knowledge. In this study the main purpose was to reinforce the play-learners' performance measurement in SGs. Accentuation on having straightforward and consistent association among apparent, observable behavior and concealed form of interest was the main point of the game telemetry. When playing SGs the target is to obtain knowledge of the specified content, thus, measurements concentrate to the learning outcomes. However, measuring performance in SGs is laborious because of the lack of direct in-game measures of the wanted outcomes. In order to discover whether learning is obtained, learning signs have to be collected by fine-grained game telemetry.

"The Dynamical Analysis of Log Data within Educational Games"(Snow, E. L., Allen, L. K., & McNamara, D. S. (2015), is a book chapter that describes the power of learners' interaction log data that represent students' performance and choices and the methodologies that quantify patterns over the playing time. This study applies dynamical analyses to log data in the game-based system iSTART-2, the Random Walks, Entropy, and Hurst exponents. Random Walks is a mathematical tool that provides visualization of pattern changes over the time and in combination with Entropy and Hurst analysis provide quantifiable measures of changes and variations in patterns over the time. Hurt exponents render behavioral changes related to what happens before and after where associated actions are meditated as persistent or controlled. On the contrary, Entropy, quantifies the level to which the integral time series is foreseeable contrast random. These three techniques contribute to an innovative way of visualization and subtle categorization in play-learners' behavioral patterns that appear in log data. Moreover, these tools may be used to visualize divergences in interaction patterns correlated to groups of individuals. We could exhibit in detail each method individually but this will lead us to a more technical description and would be out of the scope of the research question. Although, it is necessary to point out that these techniques may enlighten alterations in learners' behavior and thus on learning outcomes and that these techniques handle time as a crucial variable that enables not only the examination of aggregated interaction data but also the examination of interaction behavioral patterns that appears across time.

In the book chapter, entitled "Measuring Expert Performance for SGs Analytics: From Data to Insights", by Loh, C. S., & Sheng, Y. (2015), the authors perform among the methodology of obtaining players' generated interaction data in SGs, methods to distinguish expert and novice performance involving behavior profiling. They examine and compare course of actions of experts and novice players by means of "Expertise Performance Index" metrics which categorize players by SGs competency levels. Researchers retrace the course of players' in-game actions in order to visualize navigational paths and find out meaningful patterns. Once interaction data is collected, data mining techniques as data cleaning, analysis, and visualization are applied. Then analysis may reveal students' profile characteristics, compare players' behavior, classify gameplay patterns and finally identify concealed patterns of players' behavior. Moreover, different techniques were used to assess students'/players' performance such as Bayesian Networks but proved to be not suitable for all kinds of SGs. On the contrary cluster analysis enables players' categorization according to their in-game course of action and the analysis leads to prescriptive use of players' in-game data. When experts' and novices' players' course of action are available, their similarity will be obvious while comparing these courses of actions. Consequently, once the performance level of experts will be considered as an expert performance baseline and the desired level of achievement of novice to compete and reach this level, then the difference in performance shall be obvious.

Westera, Nadolski, and Hummel (De Gloria, 2014) studied existing log files of VIBOA serious games. Their purpose was to investigate to what degree logging data of serious games may uncover significant patterns, variables, and relations. The studied serious games enable freedom of movement on that basis behavioral variability was found. They used the EMERGO open source environment to aggregate and integrate logging data to a joint logging file. This file consists of students' in-game actions that uncover identifying characteristics and variables. Authors discovered learners' "switching" behaviors as actions characteristics when they researched to what degree identification of distinguished behaviors are obvious. Having the result of "switching" behaviors they applied predictive regression models with the usage of certain switching rates as learning obtainable predictors to find out whether behavioral characteristics are the predictors of final assessment scores. They discovered that switching behavior situated on certain rates such as video and location access rates can predict 54% of learning ability. Then they applied statistics to switching behaviors concerning the total time spent but found weak correlations to support the outcome of predicting final score.

Ninaus et al. (2014) try to find neurophysiological patterns that will comprise a baseline metric for discovering if players-learners actually learn while they are playing. They applied neurophysiological methods to study brain activation patterns. Neurophysiological signal may reveal students' progress while they are playing SGs. They claimed that the integrated algorithm of neurophysiological signals with learning analytics framework shall distinguish perceptual processes while learners interact with SGs. This means that if a student is still learning the displayed information won't change. Conversely if the algorithm observes brain activity that indicates that the player ceased learning. This approach may contribute to personalized learning.

According to Loh & Li (2016) SGs can be used to prescribe training. In their study they represent how players' in-game actions and attitude may contribute to the learners' performance improvement and to the prediction of their actions. SGs with use of analytics and telemetry methods can measure learners' in-game behaviors and transform them into gameplay action decision (GAD) profiles. These profiles can be used as patterns to prescribe training exactly when and to whom needed. Authors based their methodologies on the studies of measuring similarity among expert/novice and metrics to differentiate the performance. The learners' in-game interaction data was transformed into course of actions (COA) and comparison methods were applied so as to discover learners' patterns/profiles. Players in the beginner level were perceived as novices, as they proceed through repeated actions their expertise levels grow to competent and proficient levels. Their course of actions was illustrated as strings and was compared pairwise with expert's COA using cosine similarity to represent their performance. Three different GAD profiles were found: fulfillers, explorers, and quitters. Gameplay action decision profiles were studied by the in game routes players followed and the time they spent to accomplish the tasks, as well as the scores. The differences among the profiles were distinguished mostly by the strategy they applied to solve problems. The fulfillers tended to follow same in-game routes, contrary to explorers who switched thought routes that presented crisscross patterns. The quitters seemed to quit the game quickly enough. The authors used Maximum Similarity Indices (MSI) score to measure learners' performance and visualize results using heat maps to depict general performance of three profiles. This visualization graph shows that explorers fulfil their tasks spending less time than fulfillers despite the fact that their MSI score performance was slightly different. This means that explorers can be considered as expert profiles and could be used as expert performance baseline. Quitters stopped playing for different reasons; their early identification would help to find a way to motivate them. When stockholders acknowledge how players take in-game decisions, they can optimize learning paths and game events to maximize learning experience so as to achieve learning goals.

Another study of log files conducted by Wim Westera et al. (2014b) published in a paper entitled "Serious Gaming Analytics: What Student's Log Files Tell Us about Gaming and Learning" is similar to the study by De Gloria (2014). The authors based their study on the examination of existing log files of a SG called VIBOA; it is a 50h master level SG provided for exploration learning where students espouse environmental consulting role in order to handle complex problems. Authors applied learning analytics to 118 master students log files to obtain meaningful patterns. They used correlation analysis for identification of behavioral patterns that basically are measurements of so-called “switching” in-game interactions. They found a model that can predict learning efficiency by utilizing the “switching” indicators.

Serious games leave behind data trails, student’s choices, behaviors, and achievements, and with learning analytics techniques valuable knowledge can be obtained for various stakeholders. However, there is a difference among in-game performance and learning, high score does not necessarily imply learning. Learning is accomplished by a chain of interactions, repetitions, evaluations. SGs offer freedom of playing options/paths so while in-game learning becomes complicated and the behavioral variability increases, the information of individuals obtained learning tends to decrease. Consequently, players’ interaction data shall be analyzed appropriately to derive insight of individual’s performance and confirm the efficiency of learning. Authors pointed out the study of (Hung et al., 2020) where Hung, Hsu, and Rice consider LA as a continuation of questionnaire-based course assessment. They propose a framework where combination of students’ learning logs, demographics data and final assessment surveys were used for programme evaluation. This approach based on factor analysis and decision tree analysis enables thorough assessment and offer prognosticative models of lesson content, teacher content and final grades.

Except from logging data, authors gained access to the students’ final examination scores which they used in combination with discovered behavioral patterns for association of learning effectiveness. Serious Games logging analysis is divided in two types, the in-game logging analysis and the posterior logging analysis. The in-game analysis uses students’ individual interaction data. These data is being constantly evaluating so as to offer dynamic adaptive and personalized players’ experience. The posterior logging analysis is applied to aggregated log files for purposes of quality evaluation and improvement, behavioral patterns identification. This offline process is applied to the current study. Researchers defined appropriate variables for their analysis of logging data, the variables concerns time spent in game, number of locations visited, number of resources opened, number of videos opened and time spent on them, pre-test number of answers, and examiner final marks. Applying statistics they discovered average values for each variable such as in-game time spent per student, standard deviation, and coefficient of variation. Then they used total time in concerns with various in-game activities and assigned rate variables (final score per unit time, user action per unit time, access rate locations/T, access rate resources/T, access rate videos/T) values again average per student, standard deviation, and coefficient variation. Finally they measured Spearman correlation between rate variabilities and represented rates as final score, user action, access location, access resources, and access videos. The results indicate behavioral invariability among the rates of acquired learning, user actions, location accessed, resources accessed, and videos accessed. Correlation and variance shows students' "switching behavior" as their behavioral distinguished features.

To identify whether behavioral traits can be perceived as predictors of final scores or learning outcomes, researchers applied numerous regression analysis to discover connections among "switching rates" and final examination scores. Based on time activity rates authors displayed the obtained learning as scores per unit time, which depict the learning efficacy. They developed linear models of hierarchical regression, one of which represents greatest results where switching behavior seems to be partial predictor (62%) of learning efficiency. However, the connection among scores and total time spent didn't come out strong enough to infer knowledge. The authors came to the conclusion that switching behavior which is based on video objects and overall activity rates comprise a predictor of learning efficacy.

Almost all the reviewed studies (Freire et al., 2016), (Minović & Milovanović, 2013), (Pereira et al., 2016), (Shoukry et al., 2014), (Cariaga & Feria, 2015), (Harpstead et al., 2014) make references on identification of behavioral patterns which could be associated with learning outcomes. When learning analytics are applied in serious gamers, an in-depth analysis of interaction student's data may reveal useful patterns. These studies don't exhibit a thorough analysis of the research question.

In the study by *Chaudy et al. (2014)* the authors describe an assessment engine that is useful for educators and developers. The learning analytics part of the engine enables teachers to control SGs and their students through learning analytics reports. This part contains data from a configuration file such as student's meaningful characteristics, learning outcomes, activity, and feedback. The learning analytics dashboard permits teachers to refine the discovered data by gender, age, country. In case that educators believe that they need supplementary characteristics in order to identify new patterns they may append them by using a visual language. This addition will not be visible automatically by the system but a new version of the game will be produced including this new field, and therefore the learning analytics interface will be updated.

Summarizing, the learning analytics reference model shall be considered in the early design stages of SGs, and questions included in this model shall be answered. What type of data shall be gathered for analysis, who is the stakeholders of the analysis, why the data shall be analyzed, how the data shall be analyzed? The prediction model shall reveal future learners' performance and knowledge based on learners' present actions and achievements. Therefore to predict learning outcomes it is essential to build the learner's profile. SGs are perfect environments for behavioral identification patterns and with LA techniques marvelous outcomes may be achieved (Chatti et al., 2012).

The reviewed studies are summarized by the techniques and methods in the following tables; 4-1.Prediction of learning outcomes and 4-2.Behavioral patterns identification. Studies categorization shows that the behavioral patterns reflect students learning outcomes, as well as distinguishing expert-novice performance including behavioral profiles. Player's performance assessment can be measured by defining performance variables. Behavioral patterns can be identified by studying players' course of actions and applying data mining and analysis to the in-game interaction data.

Table 4-1: Prediction of learning outcomes

Techniques		
Bayesian Network	(1 study)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Correlation analysis & regression analysis	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014). Serious gaming analytics: What students log files tell us about gaming and learning.
Data mining	(1 study)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Entropy analysis	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In *Serious games analytics* (pp. 81-100). Springer, Cham.
Game telemetry	(2 studies)	Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham.
		Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Hurst exponents	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In *Serious games analytics* (pp. 81-100). Springer, Cham.
Neurophysiological signal	(1 study)	Ninaus, M., Kober, S. E., Friedrich, E. V., Neuper, C., & Wood, G. (2014, September). The potential use of neurophysiological signals for learning analytics. In 2014 6th International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES) (pp. 1-5). IEEE.
Random Walks	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In *Serious games analytics* (pp. 81-100). Springer, Cham.
Predictive regression model	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2013, October). Learning analytics in serious gaming: uncovering the hidden treasury of game log files. In International Conference on Games and Learning Alliance (pp. 41-52). Springer, Cham.
Methods		
Behavioral patterns' impact on learning outcomes	(3 studies)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham.
		Westera, W., Nadolski, R., & Hummel, H. (2013, October). Learning analytics in serious gaming: uncovering the hidden treasury of game log files. In International Conference on Games and Learning Alliance (pp. 41-52). Springer, Cham.
		Westera, W., Nadolski, R., & Hummel, H. (2014). Serious gaming analytics: What students log files tell us about gaming and learning.
Compare and contrast outcomes	(1 study)	Smith, S. P., Blackmore, K., & Nesbitt, K. (2015). A meta-analysis of data collection in serious games research. In Serious games analytics (pp. 31-55). Springer, Cham.
Differentiate expert-novice performance icluding behavioral profiling	(2 studies)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
		Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Measure players' performance	(2 studies)	Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham.
		Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.

Table 4-2:Behavioral patterns identification

Techniques		
Cluster analysis	(2 studies)	Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham. Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Correlation analysis	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014). Serious gaming analytics: What students log files tell us about gaming and learning.
Cosine similarity	(1 study)	Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Data mining	(2 studies)	Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham. Smith, S. P., Blackmore, K., & Nesbitt, K. (2015). A meta-analysis of data collection in serious games research. In Serious games analytics (pp. 31-55). Springer, Cham.
Entropy analysis	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham.
Expert/Novice course of action (COA)/profiles	(2 studies)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham. Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Expertise Performance Index	(1 study)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Game telemetry	(2 studies)	Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham. Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Hurst analysis	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham.
Maximum Similarity Indices (MSI) score	(1 study)	Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Random Walks	(1 study)	Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham.
Statistical Processes	(2 studies)	Westera, W., Nadolski, R., & Hummel, H. (2013, October). Learning analytics in serious gaming: uncovering the hidden treasury of game log files. In International Conference on Games and Learning Alliance (pp. 41-52). Springer, Cham. Westera, W., Nadolski, R., & Hummel, H. (2014). Serious gaming analytics: What students log files tell us about gaming and learning.
Visualization	(2 studies)	Smith, S. P., Blackmore, K., & Nesbitt, K. (2015). A meta-analysis of data collection in serious games research. In Serious games analytics (pp. 31-55). Springer, Cham. Chaudy, Y., Connolly, T. M., & Hainey, T. (2014, September). Engage: A link between educational games developers and educators. In 2014 6th International conference on games and virtual worlds for serious applications (VS-GAMES) (pp. 1-7). IEEE.

Method		
Compare patterns	(5 studies)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham. Chung, G. K. (2015). Guidelines for the design and implementation of game telemetry for Serious Games Analytics. In Serious games analytics (pp. 59-79). Springer, Cham. Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham. Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham. Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Retrace COA	(1 study)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Identify concealed patterns	(1 study)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham.
Identify expert and novice performance	(2 studies)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham. Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Identify neurophysiological patterns	(1 study)	Ninaus, M., Kober, S. E., Friedrich, E. V., Neuper, C., & Wood, G. (2014, September). The potential use of neurophysiological signals for learning analytics. In 2014 6th International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES) (pp. 1-5). IEEE.
Measure performance	(2 studies)	Smith, S. P., Blackmore, K., & Nesbitt, K. (2015). A meta-analysis of data collection in serious games research. In Serious games analytics (pp. 31-55). Springer, Cham. Loh, C. S., & Li, I. H. (2016, October). Using players' gameplay action-Decision profiles to prescribe training: Reducing training costs with serious games analytics. In 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 652-661). IEEE.
Patterns classification	(2 studies)	Loh, C. S., & Sheng, Y. (2015). Measuring expert performance for serious games analytics: From data to insights. In Serious Games Analytics (pp. 101-134). Springer, Cham. Snow, E. L., Allen, L. K., & McNamara, D. S. (2015). The dynamical analysis of log data within educational games. In Serious games analytics (pp. 81-100). Springer, Cham.

4.2.2 RQ2: Could commercial games analytics be useful for serious games learning analytics?

Game analytics (GA) is a terminology used by the commercial game industry to utilize analytics for game development and research purposes. GA aims to acquire insight of payers' experience through players' in-game actions and to improve game design and increase game expansion. Developers confront challenges to produce an amazing players' experience game. Tracking players' interaction data gives the chance to gain knowledge on the way customers are playing and thus steer toward the improvement of players' experience and the income growth. The data collected by GA vary in type, contingent on the game domain, technical that pertain to the game mechanics and design and the user data that concerns user gameplay experience. Technical type position is to acquire metrics that will improve game development; these metrics are errors in code, fixation time, and errors concerns hardware and software performance metrics to ensure the steady gameplay execution. From an User-oriented viewpoint, GA concentrates on user interaction data which may be customer metrics, community metrics, and game metrics. Customer metrics refers to players' transactional attitude in the game and outside the game. Community metrics involves players' interaction measurements in forums, customer service and others related to communities. Finally, game metrics measure players' in-game interactions. These metrics of GA can be used by serious games as both entertainment and SGs are a perfect environment which produces a vast amount of players' interaction data. Moreover, the game industry uses telemetry methods for non-intrusive interaction data collection. The analysis of the collected data with data mining techniques reveals valuable insight of the game; difficult or easy instances of the game that shall be improved, unapproachable areas or popular areas of the game where targeted advertisement may affect earnings. The aforementioned GA techniques aim to offer a greater players' experience and give valuable chances if united in educational games (Freire et al., 2016).

According to the study of Wim Westera et al. (2014b) commercial games companies use posterior logging analysis to evaluate players' choices, to track in-game bottleneck, to make prediction for players' in-game actions. This type of analysis can be used by serious games researchers to accomplish connection among gaming and pedagogy.

The study by Loh & Li (2016), makes reference of U.S. Marine Corps which was the first organization that transformed a commercial game into a serious game for training purposes. The authors outlined the common objective of Game Analytics and Serious Games Analytics that is to maximize the value of player data but SGA has additional purposes of performance estimation, evaluation, and improvement.

The study by Callaghan, McShane, & Eguiluz (2014), represents a pragmatic example where game analytics and metrics are used for the intention of education and teaching. The study presents the way that commercial games engine, Unity3D, is being used to model simulations for teaching a particular educational domain of electronic circuit theory. The game is developed so as to engage students and to measure their engagement and retention with the use of analytics. Game analytics were applied in two types; core and custom where core provide standard metrics such as active users, time, time spent in session etc. and custom analytics that were based on educational needs to obtain detailed in-game information of students interaction so as to measure students' engagement and retention.

It is clearly stated that Game Analytics (GA) can be useful for Serious Games Learning Analytics (Á. Serrano-Laguna et al., 2017). The study represents an interaction model along with the SGs xAPI profile in order to define standards to systematize LA in SGs. Commercial games have been depending on game analytics for a long time. Game analytics researchers rely partially on questionnaires to appraise game design or gameplay but mostly they depend on the in-game interaction data gathered from the embedded tracking methods usually referred as telemetry. This tracking system traces in a non-disruptive way all kind of interactions for various objectives from income prediction to the engagement measurement. Serious games could greatly take advantage of game analytics techniques and non-disruptive tracking to make analysis improvements by using standards so as to facilitate learning analytics integration and their uses in education. However, commercial game industry shelters their game analytics methods and the game analytics interests differ from learning analytics purposes. Game analytics target to players' engagement, retention and to increase revenue, while in contrast learning analytics strive for analyzing and measuring players' obtained knowledge.

Therefore, the selection of game analytics techniques and elements that could benefit SGs analytics shall be considered carefully.

Serrano-Laguna et al. (2018) present a study that refers to the necessity of combining Learning Analytics (LA) and Educational Data Mining (EDM) with the Game Analytics' (GA) non-disruptive methods in order to offer trustworthy, automated and recurrent appraisal for SGs. GA among other measurements, stresses on in-game play balance measurement so as to keep players challenged, interested and satisfied. GA enable the game industry to know when players meet difficulties to move on in the game, when players drop out, and whether the game design needs improvements and how to improve it. In the design and implementation phase authors used commercial game methodologies to separate the game environment to safe and unsafe sub steps differentiated by level of difficulty. They extended the methodology into a game design pattern and also added learning elements. Moreover, they added a trackers component to capture gameplay interaction data as a commercial game does for game analytics purposes. Consequently, commercial game analytics can be useful for serious game learning analytics.

Except from game analytics benefits for serious game learning analytics there were studies that referred to the uses and benefits for SGs of the commercial games development tools. As a matter of fact the study "Tools and Approaches for Simplifying Serious Games Development in Educational Settings" (Calvo et al., 2016), represents various commercial development tools and their advantages and disadvantages in deploying them for SGs development. Worth to mention that authors pointed out that commercial Off-the-Shelf (COTS) games when used in an educational setting are a more economical approach than developing a SG from the beginning. Nonetheless, it is laborious to find a suitable COTS game to serve specific educational requirements. Furthermore, a COTS game in an educational setting would probably need modification to offer the suitable type of game learning analytics and the proper classroom assistance that an educator would presume as default in authentic SGs. Although, it is likely to overcome this mater and count on game-play experience against traditional educational methods, the absence of in-game assessment demands teachers to make more effort that in actual SGs.

Another example of merging the commercial gaming experience and tailored educational tools is the study of "uAdveture: The eAdventure reboot" (I. J. Perez-Colado et al., 2017). The authors refer to the fact that the available commercial games may be in some cases suitable for teacher's needs. The appropriate COTS games when employed in sufficient educational settings may have relevant effect. The game called ZOO Tycoon has focal points on constructing and operating successful zoo scenarios, players learn notions that refer to economics and business management; the game was used as a SG to assist teaching in these concepts. It was another economical approach where a commercial game was used as is in education. Nevertheless, once again educators have to spend additional effort to adjust the game to educational settings, to plan pedagogical scenarios in order to deploy the game as an SG.

To recapitulate, there are definitely GA methods and practices that may contribute to the serious game learning analytics. In Table 4-3 the goals and techniques that are used in both GA and SGs learning analytics are summarized and in the Figure 4-4 they are being compared.

Table 4-3: GA Analytics compared to SGs Learning Analytics

GA Analytics			
goals			
	assess players' preferences	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
	engagement & retention measurement	(1 study)	Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017).
	improve game design	(4 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Westera, W., Nadolski, R., & Hummel, H. (2014). Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
	Increase incomes	(2 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017).
	maximize player experience	(3 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018). Calvo, A., Rotaru, D. C., Freire, M., & Fernandez-Manjon, B. (2016, April).
	maximize the value of player data	(1 study)	Loh, C. S., & Li, I. H. (2016)
	predict in-game actions	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
Techniques			
	data mining	(1 study)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016)
	metrics associating game and players	(3 studies)	Callaghan, M. J., McShane, N., & Eguiluz, A. G. (2014) Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
	posterior logging analysis	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).

telemetry for tracking interaction data	(3 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
SGs Learning Analytics		
goals		
assessment	(4 studies)	Westera, W., Nadolski, R., & Hummel, H. (2014). Loh, C. S., & Li, I. H. (2016) Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018). Calvo, A., Rotaru, D. C., Freire, M., & Fernandez-Manjon, B. (2016, April).
assessment of SG effectiveness	(1 study)	Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
game improvement	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
improvement (students' aquired knowledge)	(1 study)	Loh, C. S., & Li, I. H. (2016)
maximize the value of player data	(1 study)	Loh, C. S., & Li, I. H. (2016)
measure learning outcomes	(1 study)	Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
measure students' engagement & retention	(1 study)	Callaghan, M. J., McShane, N., & Eguiluz, A. G. (2014)
performance measurment	(1 study)	Loh, C. S., & Li, I. H. (2016)
provide feedback	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
Techniques		
data mining	(3 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Westera, W., Nadolski, R., & Hummel, H. (2014). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).
in-game logging analysis	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
metrics associating game and players	(2 studies)	Callaghan, M. J., McShane, N., & Eguiluz, A. G. (2014) Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016)
posterior logging analysis	(1 study)	Westera, W., Nadolski, R., & Hummel, H. (2014).
telemetry tracking interaction data	(3 studies)	Freire, M., Serrano-Laguna, Á., Manero, B., Martínez-Ortiz, I., Moreno-Ger, P., & Fernández-Manjón, B. (2016) Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Serrano-Laguna, Á., Manero, B., Freire, M., & Fernández-Manjón, B. (2018).

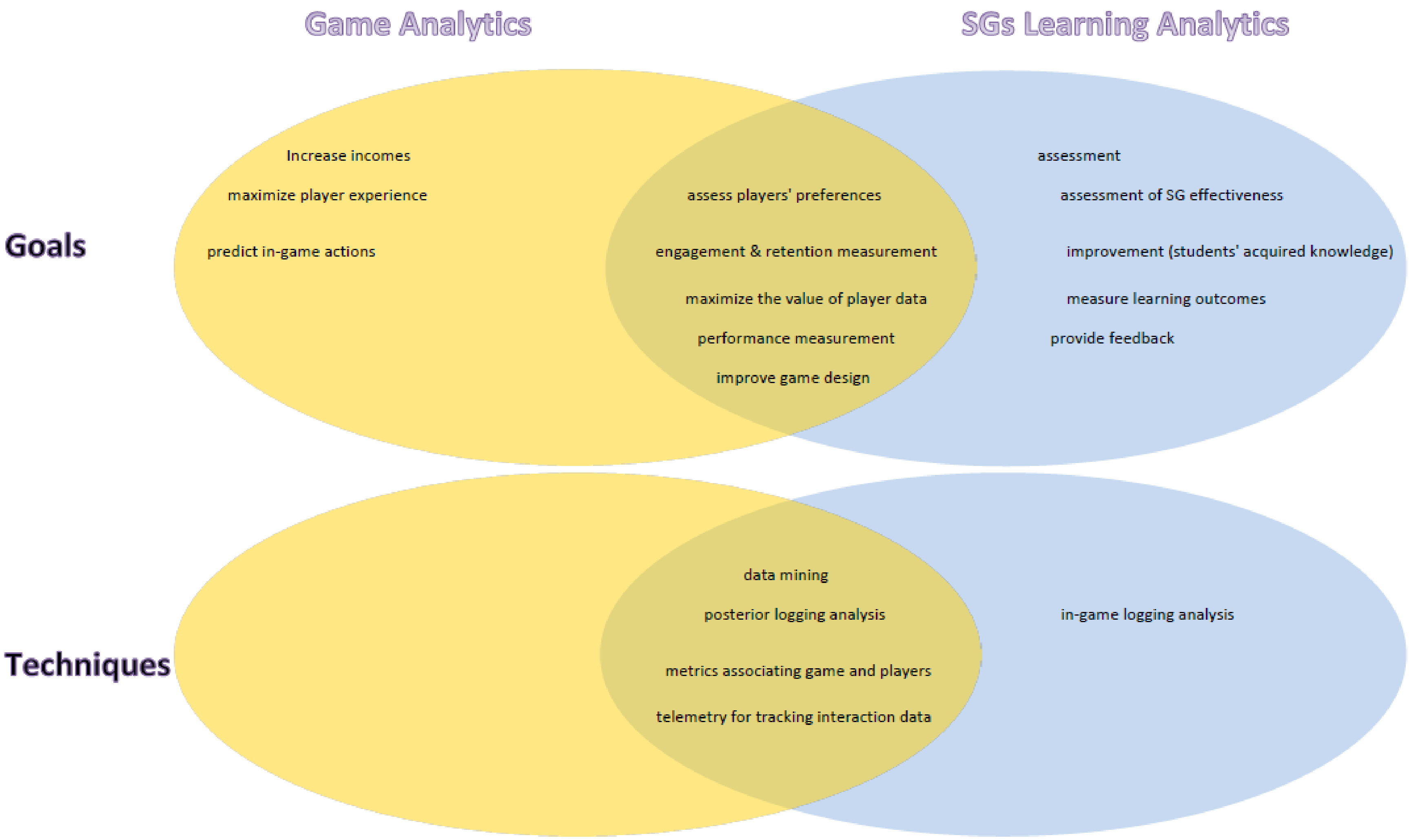

Figure 4-4: Comparison of goals and techniques og GA and SGs Learning Analytics

4.2.3 RQ3: Are there defined methodologies for implementing LA in SGs?

Despite the adoption of serious games in educational environments there is still a lack of a general standardized approach for implementing learning analytics in SGs. A simple and transparent methodology of the SGs' full life cycle from early development stages (design, development, validation, deployment and repeated refinement) to the final use, is necessary so as to simplify SGs acceptance. Unfortunately, nowadays game learning analytics are usually implemented for each case individually through ad-hoc solutions. In the study of "Full Lifecycle Architecture for Serious Games Integrating Game Learning Analytics and a Game Authoring Tool" (Alonso-Fernandez, Rotaru, et al., 2017), authors perform three main points: LA integration with a game authoring tool (uAdventure), the standardized trace collection with the use of the standard xAPI-SG interaction model, and finally, the default way to analyze and visualize results for the stakeholders as game developers, educators, and students. This holistic approach of development, deployment, and analytics, enables a systematic analysis and confirmation of SGs and an access to various analyses with nominal setup. Moreover, this architecture contributes to the improvement of the SGs development and assessment through an empirical approach where game and learning assessment are achieved.

LA methodologies in combination with GA techniques can be utilized to trace and analyze students' interaction data in order to obtain insight of the students' learning progress. The whole process comprises the so called Game Learning Analytics (GLA), which enable evidence based practice to the lifecycle of game. The integration of analytics in the lifecycle of SGs (Figure 4-5) is crucial for collecting and analyzing students' interaction and generates feedback.

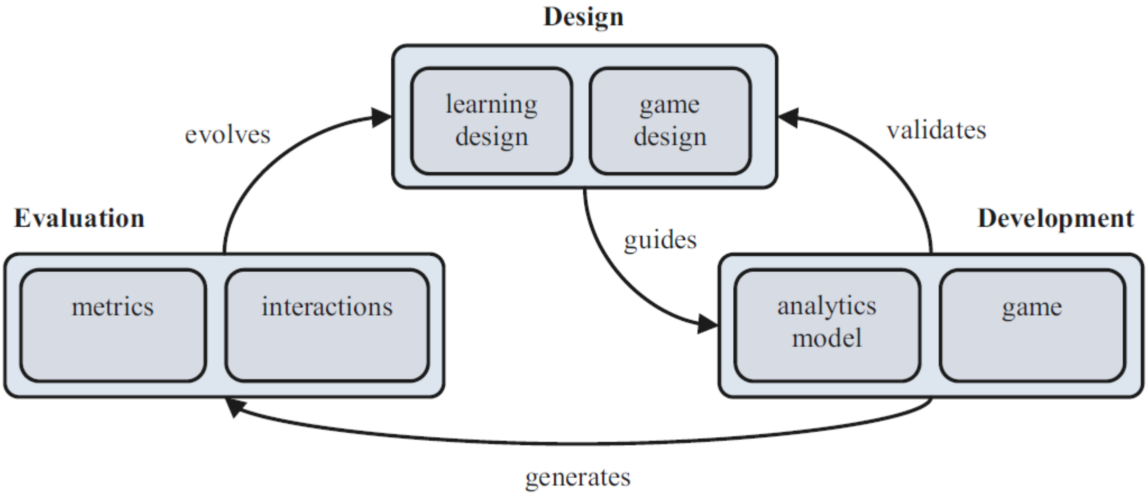

Figure 4-5: Lifecycle of a serious game: from learning and game design, through development, validation and evaluation (Alonso-Fernandez, Rotaru, et al., 2017)

The analyses at the game level and learning level that GLA offers, combine separate systems and is beneficial for early quality evaluation. The integration of analytics which is beneficial for the stakeholders (teachers and students), provide real-time knowledge of in-game actions.

The authors proposed a full and scalable analytics architecture (Figure 4-6), having used standards that enclosed the entire process from game design to the analysis and results visualization; this design drove game development, the embedded tracker component sends student interaction traces to the analytics platform which provides feedback to the learning and game design. In the depicted architecture, SGs provide traces in a desired standard format to a server where analyses take place and the captured traces transmute into meaningful information. Finally, visualization through dashboards to various stakeholders takes place.

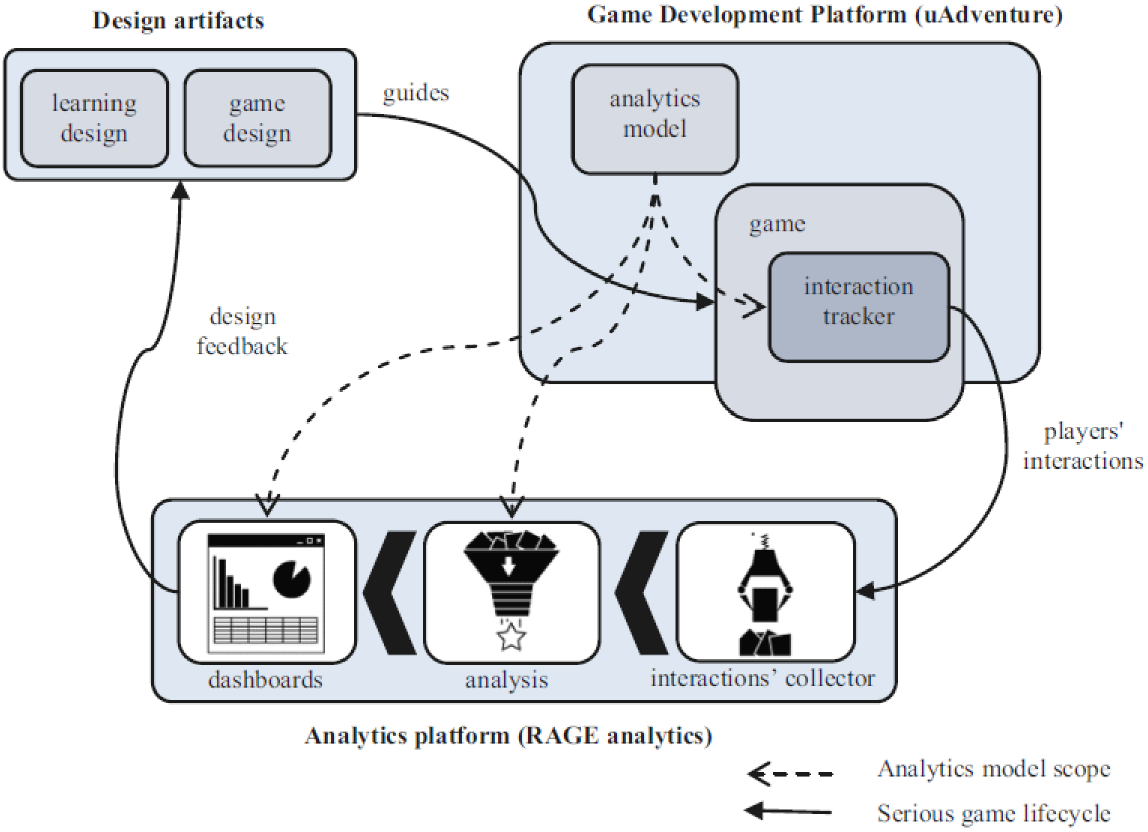

Figure 4-6: Proposed architecture: design guides game development(Alonso-Fernandez, Rotaru, et al., 2017).

The above analytics model has envisaged the fact that visualization results list shall be created in order to affirm that goals of game mechanics and learning design have been met and work in reverse to determine the appropriate analysis and data collection. The authors examine the data standards and SGs and concluded that the xAPI Serious Games (xAPI-SG) vocabulary provides a suitable format. The experience API (xAPI) format performs statements with different attributes such as an actor, a verb, an object, or a timestamp and others. The interaction model includes variables such as completables, alternatives and other meaningful variables to track interaction. The games' interaction tracker component sends players' interaction as xAPI-SG to the analytics platform. Then, the analytic model decides which incoming interactions, events are reported and the way they are assigned to their analogous xAPI-SG attributes or verbs or activity types.

An embedded analytic model that has been designed together with the SG is believed to be the best practice as both are determined by the game design. However, a default analytics model can minimize the effort of the game design and development. An already developed SG needs an external tracker and analytics model so as to integrate

GLA to the game development platform. Yet, if the game development platform follows the proposed architecture then it has to include the tracker component and set it up with an analytics model which is completely integrated with game environment. The integration will decrease time and effort for the developers and offer a possibility to improve the game design and analytics model through the game lifecycle iteration.

The collected data may be analyzed in two ways; by game-independent analysis and game-dependent analysis. The first can serve any SGs that send the compatible standards xAPI-SG statements to the connected analytics server and the second analysis has to be designed for each game separately, though enabling the creation of dashboards that meet game's purposes and design. In both cases the analytics model shall supply metrics information and KPIs that will confirm the learning design effectiveness. The analysis results are stored for visualization. The visualization is performed through dashboards for the stakeholders. The results shall be visualized in a simple understandable way and provide real-time targeted information for teachers to monitor their class and students to track their progress. In their implementation of the proposed architecture the authors used the Kibana engine directly connected to Elasticsearch for the development of the visualization dashboards. Kibana offers a web based interface for quick analysis and visualization with the available graphs and the opportunity to configure custom dashboards. Also, alerts and warnings were included in their implementation to offer real-time information to educators.

The authors (Alonso-Fernandez, Rotaru, et al., 2017) proposed a full architecture to accomplish GLA that includes all the aforementioned steps; data tracking, data analysis, and visualization of results. Their standard based architecture combines models that collaborate in order to analyze and visualize data collected from SGs. The proposed GLA system is shown in Figure 4-7. The embedded tracker component provides the collector with xAPI traces, the collector then sends the traces for real-time analysis and stores them in the LRS (Learning Record Store) for batch analysis. Finally, the visualization derived from the analytics offers feedback so as to improve the learning and game design and provide students' assessment.

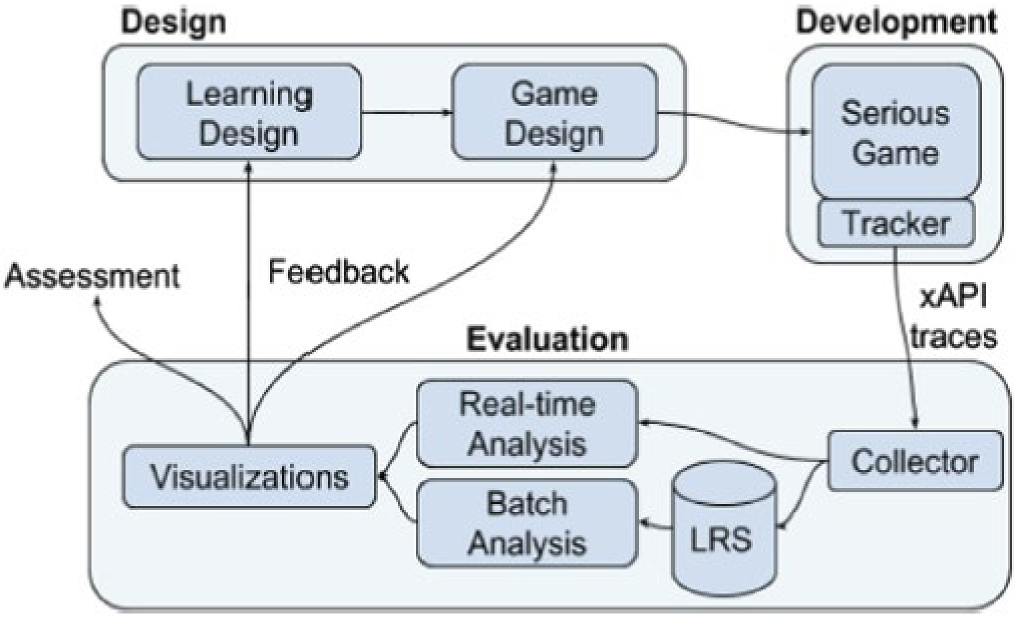

Figure 4-7: GLA system: from design to development and evaluation (Alonso-Fernandez, Rotaru, et al., 2017).

Design: Learning and game design define the SG implementation. In this stage game mechanics, structure, objectives, game characters, learning objectives by means of variables are included. The right definition of learning elements is critical as the learning evaluation outcomes depend on these variables.

The embedded tracker component sends xAPI format traces. Current tracker implementations include Unity C#, pure C# and JavaScript to simplify their integration with SGs.

xAPI-SG statements are delivered to a collector component on the server side. Then the statements are forwarded to a real-time analysis component where the players' information is updated. xAPI traces are also stored in the LRS for later analysis.

Visualization of results is available for the stakeholders through dashboards with different metrics. Alerts and warnings are also available.

The process is achieved when the obtained information provide feedback and improvement actions that can be reestablished in the system for learning and game design iterations. Students' assessment is also achievable in this stage.

The above GLA architecture has been developed as a factor of an EU H2020 SG-related project.

The study of (Alonso-Fernández et al., 2019), expose positive results of game learning analytics application. The authors identified lack of empirical studies about the SGs' learning process and tried to cover the lack by providing three SGs applications. Their empirical study shows that it is important that the game follows a learning design and provides evidence-based assessment. They followed the LAM model at the design stage so as to clearly define goals and the way that the collected interaction data achieve these goals and are adequate to provide evaluation for the SG and the students' assessment. They applied GLA with three different SGs in actual educational scenarios and for three different purposes; to validate and deploy the SG Conectado for raising awareness of bullying and cyberbullying, to validate the design of the DownTown SG to promote independence to users with intellectual disabilities, and to improve the evaluation of the First Aid Game on first aid techniques. Their study shows three different uses of GLA in SGs; design improvement, the process of evaluation and deployment. The three SGs purposely show three different aspects of GLA uses in educational settings; the SG' validation, real case deployment, and the students' assessment. They provide evidence-based insight on the precision of SG design to the desired learning outcomes for educators and researchers.

The methodology followed in the study was based on the LAM model. First they have to examine if the learning design and goals meet with game mechanics and goals, what data should be collected, how it will be collected and analyzed so as to provide meaningful visualization to the stakeholders. They used xAPI-SG standard collection model to track interaction data. They reused the xAPI tracker component and the GLA infrastructure that was developed in the H2020 RAGE project.

The case study, based on a SG called Conectado, used pre and post questionnaires to evaluate the SG. The GLA data showed metrics about game completion differentiating female and male players. Educators were able to monitor students' in game actions by dashboards visualization and were able to intervene when needed. Results contribute to the design problems identification. The SG was deployed in 8 schools and proved that SGs with advantages of GLA can be deployed in a systematic way in educational environments.

The DownTown SG trains people with intellectual disabilities to use subway transportation routes so as to travel alone in real life. The SG was tested with 51 adults.

The GLA data collected show metrics of routes, help element's uses, total game time, etc. The analysis of GLA data contribute to the SG design improvement and to the measurement of learning outcomes achievement.

The First Aid Game (Alonso-Fernández et al., 2019) was validated with approximately 300 students to teach first aid techniques in three situations. The GLA data included complitables, scores, interaction with game elements, correct/incorrect answers. The GLA application for pass/fail predictions shows that the best model was logistic regression with 89% accuracy, 98% recall, and 10% misclassification rate. Support Vector Regression was the best prediction model of scores. The GLA data features associated with predictions are the number of interactions with game characters, game level scores; that can be used as in-game action baseline for assessment purposes.

Author (Alonso-Fernández et al., 2019) considered that their study provides guidelines and benefits for future work for 3 reasons. First, the standardized GLA data collection, the xAPI-SG profile, simplifies the data collection because they easily define and match the interaction data to be collected for each of the three games with the exact xAPI-SG profile verbs and activity types. This also simplifies the integration with the Analytics System, so as to provide real-time visualization. Additionally this standardization enables real-time analysis to compare the interactions data from different games. Second, the use purposes of GLA data have proved in this study that game GLA data may be used effectively for different purposes and at different phases of SGs' lifecycle; game design validation(DownTown SG), to simplify deployment of SG and to validate SG (Conectado), and to achieve students assessment with SG (First Aid Game). Finally, GLA use in SGs benefit stakeholders. For the developers the benefit is to simplify game design validation, for educators to simplify the deployment of SGs in their classrooms, to monitor their students while they are playing and intervene when needed and even rely on SGs for students' assessment, and finally for students to learn about their progress.

The study of (Minović & Milovanović, 2013), presents a specific visualization tool for tracking students' learning progress in real game-play time. The tool was designed specifically on the bases of the students learning model and enables tracking the game progress and monitoring the learning process in real-time. Their approach uses a combination of an educational game development platform with ad-hoc data visualization for monitoring the learning progress. The main benefit of their approach was that the educational game development can be guided by a learning scenario, which practically delineates domain concepts and a learning path that a student shall adopt. They followed a model-driven development and used a platform-independent base model (PIM), platform specific models (PSM) to achieve independence of the different implementation technologies (e.g. LMS). They defined a knowledge model and integrated it into the game, enabling except from managing learning paths through the game, the reusability of knowledge, and the integration of knowledge assessment in the game. Thus, they introduced a relation among game and knowledge with the Educational Game Learning Object (EduGameLO) and Educational Game Assessment Object (EduGameAO). The association of EduGameLO and EduGameAO provide one or more domain concepts. Although, learning and assessment may overlap each other, in the introduced model authors managed to separate the Learning Object (LO) and the Assessment Object (AO). They included Andersons' taxonomy model which is the classification of learning objectives within educational settings. In order to enable learning and assessment of the same concepts on the unlike cognitive levels they developed a meta-model based on Andersons taxonomy models. The meta-models defined a Learning path model related to domain concepts. The authors' approach may help inexperienced educators to rely on the domain model in specific knowledge area, exploiting the established relations among concepts for the specified domain model. In their case study, the authors defined new or reused existed domain models in the computer networks model. Then, educators created a new adventure game in the authors' development environment. To create quest, teachers had to choose a domain model and a central domain concept. Afterwards, they had to choose one or more game objects for each quest step that could be a Learning Object, an Assessment Object or a Multimedia Object from the available game objects. Finally, the game session could start and teachers may monitor their students while playing. The visualization model of the study has already been described in 2.5.4.3 Data visualization.

The authors (Minović & Milovanović, 2013) are confident that the introduced analytics tool simplifies the educators' involvement into the game session by manipulating game activities and level of difficulty so as to improve learning outcomes.

This approach provided information of the learning process both for educators and students in an effective way.

Another approach that discusses the steps of design and game mechanics from users characteristics, accessibility requirement to the final step of implementing the games, is the study of (Cano et al., 2016). The authors, developed a SG called "DownTown: A Subway Adventure" in order to train people with intellectual disabilities to use the public transportation system. Their goal was to improve the learning process of the players in the process of acting in a self-sufficient manner. All the domain problems (cognitive/intellectual, physiological, and motor characteristics) that this population may confront were translated to game events that the players were called to solve. The authors evaluated the learning outcomes comparing groups of players, those who were trained before with videogames and those who were trained only with the DownTown SG. They also measured the performance associated with stressing situations. Game mechanics were designed carefully bearing in mind players' characteristics which were separated into psychological areas; intelligence, memory and perception, personality, biological and motor skills. These features were translated into user technical and non-technical requirements as game mechanics that influenced the learning process. These requirements included:

1) Start menu and game sessions (sessions, accessibility, and consistency)
2) Levels (level difficulty, sandbox mode)
3) Texts and dialogs (text speed, language and structure)
4) Interface (help, tasks)
5) Mechanics (time, tutorials)
6) Others (sound, camera)

The authors included a learning analytics module to track the interaction data so as to associate it with the defined requirements. Analyzing the collected data provided an insight of the learning process, of players' engagement and proved the game design effectiveness and the validation of the defined users' requirements. They divided set of traces and listed them in tables presenting parameters and objectives associations.

- Main menu parameters and objectives
- Character selector parameters and objectives
- Game sessions parameters and objectives

Actually they performed a simple way of analyzing game parameters and learning objectives so as to evaluate the learning process and game effectiveness. However, because of the cognitive condition the proposed procedure can't be fully standardized but can minimize the effort in SG development.

The authors in the study of (Harpstead et al., 2014) presented a novel technique to evaluate the SG's alignment with its defined learning goals. They applied learning analytics to students' interaction data, measuring which principle-relevant metrics can be determined along with the students' solution. Actually they reviewed how the game responded to students' solutions that followed the targeted principle or not. They used EDGE (Engaging Design of Games for Education) framework to align game design and educational goals. The framework includes educational objectives, game design theories, and learning science theories. Cluster analysis was used to distinguish students' individual solutions, so called the representative solutions. Principle-relevant metrics (PRM) were applied to evaluate the representative solutions so as to measure how close the solution was to targeted principles and to provide feedback. The representative solutions were categorized into principled and unprincipled as successful or unsuccessful solutions. This method helped authors examine game alignment.

The game was deployed in schools and played by 174 students. The interaction data was stored and replayed so as to perform further analysis. The authors defined solution clusters for each level as a representative solution for the level. Then, the average PRM of each representative solution was calculated and comparison techniques were applied. The analytical results showed that students' feedback provision and game's teaching principles were not aligned. The authors discovered that there were solutions that followed targeted principles of a game level but didn't conclude to player's success. However, the proposed approach enables designers to find which principle-relevant metrics are suitable for alignment.

The authors believe that their approach of evaluating the game's alignment is suitable for other games scenarios. However, this requires considering that the game educational objectives must rely on measurements that can be simple metrics or complicated compound metrics and that the players' solutions must be captured.

The study of (V. M. Perez-Colado et al., 2018) presented a data model that was designed for exposing location-based characteristics of in-game students' interactions in a pervasive experience to a LA infrastructure. The proposed data model was based on the xAPI profile and was extended to match specific needs. Actually, to incorporate standards-based LA for location-based SGs, the authors added specificities for supporting player movement and location-based interactions to the xAPI SG profile. They applied their solution to a case study at the Complutense University of Madrid. In their study they stressed on two types of interaction those that were based on position and those that were based on orientation. Navigation mechanics were included to show that the player reached a set of points or even passed the points. They added a location-based context in each trace so as to derive the optimized valuable information by applying LA and thus, improving the application of pervasive games. By adding location-based extensions to xAPI SG statements they achieved location-based analysis on these traces. Location extension showed the position of the player and the orientation extension showed the player's direction. Also, the guide extension was included to show navigational context that was used to guide the player. Actors and Objects of xAPI SG profile were defined according to the needs of location-based interactions. As well as verbs which were adjusted for including moving, entering and existing, looking, and following directions. To this place, the authors defined the interaction data that shall be collected. For the implementation of LA, the authors used a modified version of the H2020 RAGE project analytics infrastructure. They provided both game-independent and game-dependent analysis. The first refers to default analysis and the second to custom analysis which requires defining additional inputs. They used default heat–map and custom visualization. They pointed that assessment in location-based interaction data combine both locations and supplementary time-related information so as to assess students' behavior. This approach may reveal misconceptions and provide targeted feedback so as to improve the learning experience. The custom analysis and visualization can lead to high-level insight acquirement and to automated assessment of the learning process. The authors believed that their proposed solution is a simple location-based assessment model which could hold for other methods.

The study of (Alonso-Fernandez, Calvo, et al., 2017) described two steps towards systematizing game learning analytics for serious games. The first was the use of a standard tracking model to exchange data among SG and the analytics platform with the application of reusable tracker components that could be included in each game engine or development platform. The second was the use of standardized analysis and visualization assets that offer general information for any SG that sends traces in a compatible format. Further customization can be applied to analysis and visualization for specific games' requirements. The authors proposed a full, scalable, standards-based analytics architecture. They stressed the ways that interaction data can be transformed to useful information:

- for the game (at run-time) which includes improvement and personalized, adaptive experience
- for teachers (at run-time) to monitor and intervene when needed
- to measure learning outcomes, evaluate game, and provide feedback to players (after a game session)
- students assessment

The GLA architecture that the authors proposed has been described fully in the first reference of the research question. The methodology presented, started form the crucial point of defining clear learning goals that should be included in game and learning design as it will inform us if the learning actually occurs. Then, the generic tracker component communicates the traces in standardized xAPI statement. The statements are saved in the LRS for batch analysis and are forwarded for real-time analysis. Finally, visualization is obtained through dashboards and relevant metrics are shown to relevant stakeholders. Alerts and warnings are displayed too. The process comes to an end when the provided information is used for evaluating and improving the game learning design or for offering a personalized and adaptive gameplay experience. The obtained information can be used for students' assessment.

To systematize tracking steps they used a general tracking model in combination with the xAPI standard. They validated this model with a SG called Countrix, specially developed for this purpose. To provide suitable metrics they defined key performance indicators (KPIs). They followed personal privacy laws and regulations while collecting and storing interaction data. To systematize the analysis and visualization they defined two goals to be achieved. First, provide default analysis and visualization with optimized insight. Second, enable the addition of game specific information for custom visualization and the reuse of this visualization for SGs with common requirements. They listed the primary stakeholders for the default visualization. The tools that were used for analysis and visualization were Elasticsearch for analyzing data and Kibana for visualizing data. Personalized analysis and visualization were developed allowing the configuration and reuse of them.

In the same context the authors of the study of (Á. Serrano-Laguna et al., 2017) reviewed the state of learning analytics, data standards, SGs, the way interaction data is tracked and the metrics that can be derived of this data. On the basis of their review they proposed an interaction model that provided a basis for utilizing LA into SGs. They presented the SG xAPI profile and applied it in a SG called Countrix. However, mostly they focused on their new interaction model for tracking serious games and their application with xAPI specification. After reviewing the literature they aggregated case studies, and inferred an interaction model that was chosen as suitable for standardization. The standardization hopes to launch supporting infrastructure and to decrease LA application cost. The authors concluded that in order to assess students' performance it is necessary to use game-specific interactions additionally to common events and interactions. The interaction model that derived from their analysis resulted in event-based tracking including identifications such who and when interaction is generated. Types of targets in the interacted model divided into completables, alternatives, meaningful variables, custom interaction which can be generalized for reusable purposes. After analyzing learning analytics the authors concluded that the xAPI profile is the most suitable data and communication model for tracking users' interaction as it enables the extension of domain specific vocabularies for the needs of new learning activity types. They presented the Countrix SG that implements the xAPI SG profile, providing a real case scenario of implementing the profile with SG and analyzing the technique involving in the xAPI communication. The game embedded the xAPI tracker and was connected to a Learning Analytics framework that contained LRS.

The authors believed that the presented interaction model with the SG xAPI profile offered basic principles and opened a new path for SG analysis research.

In Table 4-4 we summarize all goals that are presented in the reviewed studies, steps that shall be followed in order to achieve a proper LA design in SGs, methods and tools for integrating LA in SGs that were found in our search, and finally case studies that presented the proposed methodologies. The majority of the studies presented similar goals of learning assessment, game effectiveness and improvement of learning outcomes and game design, feedback provision, and the insight acquisition of the learning process. All the studies included the steps of collecting data, analyzing data, and visualizing results. The majority defined clearly that educational goals shall be met with game design as well as the fact that the definition of learning goals is the first step of the process. Four studies refered to the evaluation of the process through iterations of the steps. Five studies described the embedded tracker component. Six of the studies used the xAPI-SG profile for sending statements to the LRS and provide real-time analysis. Three studies used the ElasticSearch and Kibana engine to visualize results.

Table 4-4: Methodologies for implementing LA in SGs

Goals to achieve		
game effectiveness / (improve learning outcomes)	(7 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
improvement/validation of the SGs development	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
insigt of learning progress	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
optimize learning process	(5 studies)	Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 Alonso-Fernandez, Calvo, et al., 2017
learning assessment	(8 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
predict learning outcomes	(2 studies)	Alonso-Fernández et al., 2019 Cano et al., 2016
feedback provision	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017

monitoring classroom (intervenention)	(5 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
players' retention/enagagement	(3 studies)	Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014
personalized, adaptive player's experience	(1 Stydy)	Alonso-Fernandez, Calvo, et al., 2017
Steps		
define clear learning goals	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 Alonso-Fernandez, Calvo, et al., 2017
define desired visualization results	(3 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Cano et al., 2016
design interventions	(1 study)	Harpstead et al., 2014
link learning goals and game design	(7 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
define variables/objectives to collect the right data	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Cano et al., 2016 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
trace/collect interaction data	(8 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
analyze interaction	(8 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
visualize results	(7 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Cano et al., 2016 Harpstead et al., 2014 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
evaluate the process through iterations	(4 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Harpstead et al., 2014 Alonso-Fernandez, Calvo, et al., 2017

Methods/Tools for integrating LA in SGs

embedded tracker component	(5 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
Platform-independent base model (PIM)	(1 study)	Minović & Milovanović, 2013
Platform-specific model (PSM)	(1 study)	Minović & Milovanović, 2013
Knowledge model	(1 study)	Minović & Milovanović, 2013
EDGE framework (Engaging Design of Games for Education)	(1 study)	Harpstead et al., 2014
LMS, MOOCs	(2 studies)	Alonso-Fernández et al., 2019 Minović & Milovanović, 2013
LAM (learning analytic model)	(2 studies)	Alonso-Fernández et al., 2019 Cano et al., 2016
clustering method	(1 study)	Harpstead et al., 2014
analytics platform	(5 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
game-independent analysis	(3 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 V. M. Perez-Colado et al., 2018
game-dependent analysis	(2 studies)	Alonso-Fernandez, Rotaru, et al., 2017 V. M. Perez-Colado et al., 2018
standardized xAPI statements (xAPI-SG)	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Á. Serrano-Laguna et al., 2017 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
Real-time analysis	(6 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Minović & Milovanović, 2013 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
LRS for batch analysis	(4 studies)	Alonso-Fernandez, Rotaru, et al., 2017 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017
metrics information and KPIs	(2 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernandez, Calvo, et al., 2017
visualization dashboards	(4 studies)	Alonso-Fernandez, Rotaru, et al., 2017 Alonso-Fernández et al., 2019 Minović & Milovanović, 2013 Alonso-Fernandez, Calvo, et al., 2017
Overlapping model		Minović & Milovanović, 2013
ElasticSearch	(3 studies)	Alonso-Fernandez, Rotaru, et al., 2017 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
Kibana engine	(3 studies)	Alonso-Fernandez, Rotaru, et al., 2017 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017
legal privacy issues compliance	(4 studies)	Alonso-Fernández et al., 2019 V. M. Perez-Colado et al., 2018 Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017

Empirical study

part of EU H2020 SG-related project	(1 study)	Alonso-Fernandez, Rotaru, et al., 2017
Conectado (SG aims to raise awareness)	(1 study)	Alonso-Fernández et al., 2019
DownTown (aims to train skills)	(2 studies)	Alonso-Fernández et al., 2019 Cano et al., 2016
First Aid Game (improve students' knowledge)	(1 study)	Alonso-Fernández et al., 2019
2D adventure educational game session	(1 study)	Minović & Milovanović, 2013
RumbleBlocks educational game	(1 study)	Harpstead et al., 2014
Case-Study experiment	(1 study)	V. M. Perez-Colado et al., 2018
Countrix SG	(2 studies)	Alonso-Fernandez, Calvo, et al., 2017 Á. Serrano-Laguna et al., 2017

4.2.4 RQ4: Are there any empirical studies for integrating LA in SGs?

The aim of the current research question is to present empirical studies that were found in our research. One of the studies found concentrates on a framework that guided the integration of LA mechanics in the domain of computer programming education (Malliarakis et al., 2014). The authors presented the proposed framework implementation in an educational MMORG (Massive Multiplayer Online Role-Playing Game) called CMX that they have developed for introducing computer programming to secondary and tertiary education students. Bearing in mind that computer programming is a difficult domain to teach and to learn, they reviewed the general frameworks and proposed one which included all that should be measured and analyzed in computer programming education. To incorporate LA in the developing phase of the SG, they considered whether game design and educational goals are linked. In this context the game was carefully designed to provide the necessary feedback from teachers and students in order to evaluate if the desirable educational goals were met. This, enabled teachers to reconfigure the game in cases the students' progress results were unsuccessful. The game features were categorized in six main axes that represented the game's measurable features that fed a mathematical model for games' efficiency measurement. The axis of the framework contained activity metrics, session time and last access, assessment methods, errors, collaboration metrics, and engagement and performance metrics. They worked out on each axis and described all the relevant aspects recorded in the game and could be used in LA. Except from students' interaction data that provide insight of the learning progress, students' in-game behavior comprises an additional way to infer conclusion. For the proposed framework implementation the authors created a mathematical model. This model provided automated results gathering and inference making with the help of LA. The values gathered for each task were measured incrementally and each rating vector was stored within the environment.

Another study that presented the development of an SG but in the domain of computer architecture learning, applied learning analytics to evaluate the game (Tlili et al., 2015). The LA results showed:

- The game effectiveness in teaching the specific domain subject
- The differentiation in gender for support during the learning-playing process
- The design improvement for some game learning activities in order to draw students' attention in learning-playing process
- The necessity to include more motivated game elements in the learning-playing process.

The authors developed a role playing SG, called Computer Architecture Game (CAG) in order to engage students in learning computer architecture. A rewarding system was used to encourage and to boost students' confidence. To evaluate the game's effectiveness, learning analytics were applied in three steps: learning-playing for 30minutes, traces collection for 15 minutes, and the final step of analysis lasting 45 minutes. The visualization results provided feedback to educators to evaluate the game and the learning process. One of means that were used to measure the impact of CAG on students' obtained knowledge was pre and post-tests. The other tool was SPSS (software for advanced statistical analysis) which was used as a learning analytics platform. The collected traces which were test traces (grades from pre and post-traces) and in-game traces were analyzed using SPSS. The method provided knowledge on enhancing the learning process by classifying students in five groups by the grades obtained. The results showed that the game improved students' obtained knowledge of the domain. Further analysis was applied to distinguish differences based on the learners' gender. Results showed that female learners made slow progress and needed further support contrary to male who succeeded significant progress in obtained knowledge. In addition, the analysis of the game learning activities showed that some activities weren't fully used by the players which leaded to the conclusion that these activities must be improved. Metrics to evaluate the quitters were applied using time spent in the game. The results showed that female quitters are more than male.

After the above learning analytics application the authors exposed recommendations for enhancing learning while using SGs:

- Game interaction data shall be stored and analyzed in order to infer knowledge of the learning process and to intervene when needed. However, it is strongly advised to specify and determine what is going to be traced and collected before applying LA.
- SGs design with integrated LA shall provide a smart learning environment. LA in SGs may personalize the game learning content and provide an efficient and adaptive learning process.
- Define clear, noticeable, reachable learning activities in the design phase of the game and include motivational elements to engage students' retention.

An interesting approach that focuses on students' assessment is presented in the study (Chaudy et al., 2014). The authors developed an assessment engine which proved to be useful for both developers and teachers and which provides a way to establish communication between them. Using a SG as an assessment tool requires the involvement at the design phase of both teachers as an expert of educational domain and developers as technical experts. The engine, EngAGe (Engine for Assessment in Games) is believed to save time and money for incorporating the assessment process in SGs. It can be used as a tool for assessment and to guide SG's assessment features. The engine is flexible as it differentiates the game mechanics and the assessment logic. It uses a Domain-Specific Language (DSL) to describe assessment configuration and web services to retrieve information from DSL (parse DSL) and conduct the assessment.

To develop a SG with EngAGe requires defining the assessment in a configuration file which is a game independent file. The file was formatted in DSL, which enables the required domain knowledge, the SG assessment, to be translated into a programming language. In this way educational experts are concentrated on the engine. Developers have to establish a link between the game and the assessment engine and follow the guidelines of assessment features. The DSL has semantics and syntactic rules, while some of the semantics were made optional so as to be more adaptable in the majority of SGs. The DSL divides the configuration file into 6 parts; SG (compulsory), learning outcomes (compulsory), player (optional), feedback (optional), actions (compulsory), feedback model (optional). Web services were used in order for the engine to be able to parse the DSL formatted configuration file. Xtext, an Eclipse tool was used for this purpose. Web services situated as most appropriate in the proposed architecture. A web service can be used for any application with any programming language simply by calling the service. It enables the storage of the collected data and the later analysis so as to distinguish game and learning problems, and learning patterns. The architecture of the proposed solution involves the engine, the resources (database), and web services.

The authors applied their solution in a pilot study and concluded that: the DSL serves the aim of clearly defining game's dimensions; the DSL profile is easily understandable; the evidence model needs improvement; the configuration file quality is a fine indicator of game's learning goals; the necessity of an editor for SG developers.

Learning Analytics can be applied to enable educators to customize the assessment. A web interface linked with the engine provides teachers an easy way to manage the SGs and their students. A LA visualization report provides insight of in-game actions, learning outcomes and feedback. Educators are capable of refining the acquired data by gender, age, and country. To apply additional characteristics so as to find new patterns, educators may intervene by adding them. Except from students' assessment, game's assessment is obtainable. Moreover educators can intervene in the assessment process by configuring the DSL configuration file using a visual language that is provided by the teacher's web interface.

Another study that proposed a model for integrating learning analytics in serious games was carried out by Hauge et al. (2014). The authors emphasized the consequences of LA in SGs and their impacts; game quality improvement and game progression, player's assessment and monitoring, player's performance and engagement, achievement of the learning goals. They presented two models of SGs analytics; the in-game real time analytics and the post-game off-line analytics. The collection and analysis of interaction data can be achieved in two ways:

- In-game analysis includes the collection of player in-game data which is analyzed in-real time in order to provide immediate assistance when required and personalized game learning experience.
- Posterior off-line analysis includes the collection of player in-game data in order to evaluate and improve game design.

The scope of the two methods differs but the collected data type is almost the same. However, it is strongly advised to incorporate LA in the initial phase of game design and to clarify and contain a semantic layer which will be linked with sub-symbolic actions so as to provide meaningful elements of game play associated with educational game design. To achieve an assessment approach, behavioral indicators must be linked with learning goals, activities, and assessment criteria.

The authors (Hauge et al.; 2014) developed a LA general framework and a data service for connecting LA and SGs, the Game and LEarning ANalytics for Educational Research, (GLEANER). The approach enables tracking and analyzing in-game students' interaction data. It has two parts; the Learning Analytics Model (LAM) and the Learning Analytics System (LAS). The LAM includes steps and information of each step whereas LAS implements the requested functions of the model. The LAM and LAS consist of five interchangeable components that collaborate in the models' workflow. The workflow includes data selection, data aggregation, data reporting, data evaluation, and game adaption. The LAS component works as a service for collecting game generated traces and can be located remotely. The game provides information to the server and makes them available for the stakeholders to monitor players' achievements. The main point was to link educational goals with in-game perceivable data and its collection.

The authors (Hauge et al.; 2014) presented an example of off-line analysis that was applied to the games called VIBOA. The VIBOA-games were developed with the EMERGO SG engine that already provided tracking and aggregation of data, thus the first two step of the GLEANER model (collection and aggregation) were typically playing the role of a relational database. Due to the off-line analysis, they didn't implement an analyzer but instead they used SPSS for processing and reporting data. The evaluation, the fourth step, was implemented so as to analyze players' preferences, bottlenecks, and variability in behavioral patterns. The final step of adaptation deals with technical changes for connectivity. The authors believed that their proposed approach enables teachers to adopt it due to its user-friendly tools.

The study of (A. Serrano-Laguna & Fernandez-Manjon, 2014) presents a way to simplify SG deployment in educational settings by the application of LA. Actually they presented SG as class exercises and intended to facilitate the teachers' task by offering real-time information of students' game play actions. Their approach included four steps so as to deploy an SG, beginning from the definition of game educational goals, the game design that captures the goals, link game interactions and educational goals, and establish data collection and visualizations of results information to assist teachers. They developed a game for XML markup language in order to replace it with exercises in Web Technologies class.

The aforementioned approach has elaborated in four steps: educational goals definition, game design and implementation, interaction analysis, and results visualization. Educational goals comprise the core of the approach. Educators must outline clear, concrete and accurate goals, starting with general and proceed into sub-goals. The game designers support teachers in this step as they hold the knowledge of translating the goals into the game. In the game design and implementation step, the content of the goals guides the game mechanics. Teachers participate in the process to validate the educational approach. The step of translating game interactions into goals achievements is tied up with game design. Two things have to be solved; first, the game designer has to determine how to transmit data to the teachers and second, teachers and designers must decide which exact interactions validate the students' accomplishment of the goal. However, the analysis of the results can be implemented in two ways; the in-game assessment where teachers receive final results and external analysis where the game sends interactions to an external component for collecting and analyzing data and displaying the results to the teachers. In the third step of visualization, relevant reports with feedback and students' performance information are available for teachers. Students may also reach auto-evaluation reports.

The authors (A. Serrano-Laguna & Fernandez-Manjon, 2014) applied their approach in a puzzle game about the XML markup language content. First, they defined educational goals which were the same with the substituted exercises. Then, in the game design and implementation phase the educational goal of writing an XML document was displayed as a puzzle game. In the next step of translating game interaction into goal achievement, two types of interaction were applied; the phase completions and introduction of XML documents in text area. The visualization step included report of individual students' performance and provided feedback for teachers to support their students. Students may also monitor their progress. The game was deployed and played by 34 students who seemed to enjoy the game as they remained active in the whole process.

The main objective of the approach was to provide real-time assessment data to the educators, which they achieved by applying the approach to a case study.

The study of (Ali et al., 2017) presented the use of SGs with integrated LA in the domain of product marketing. The authors demonstrated a case study by applying LA in a SG in order to visualize how the collected data may produce meaningful information in product marketing. The aim of the approach was to reduce time and marketing cost by means of LA application in SG. However, the study didn't display the implemented tool, but instead it presented a flowchart of the developed game logic. The description of the game story, gameplay, entertainment goal, learning goals, and possible benefits were provided. The study described what was being collected based on learning goals and presented a workflow of the learning analytics method. The workflow included the game engine, data generation process, and capture related data process, aggregate, and report processes. The developed game called Grab the Drink, targeted to provide information for marketing purposes such as direct customers' reach, promote a product and get feedback of the promotion, acquire customers preferences. The game was played by randomly selected students who could either download the game on their android mobile phones or played the game on web browsers. The collected data was analyzed and conclusions were inferred. Preferences of the drinks were shown categorizing players by age and gender. Although, LA methods of collecting, measuring, analyzing, and visualizing were applied, the integration hadn't been mentioned.

The study of (Cariaga & Feria, 2015) demonstrated a learning analytics model which was applied in a game-based learning environment. The authors developed a game for iOS devices integrating the proposed LA model. They reviewed the current state of LA models, compared the proposed model and concluded to their new conceptual LA framework. The framework included the educational game which generated the interaction data, the data events which is the collection of the data and events, and the learning analytics system. Educational game consists of the game and learning mechanics and the user profile. The LA system consists of a database, option and goals where data selection, aggregation and analysis take place, and a reports component for results visualization. The collection of the data is based on the learning goals of the game. The authors validated their framework in a SG called Kinespell. The game has visual, auditory, and kinesthetic attributes and aimed to teach spelling. The flow of the game was modified according to the LA proposed framework. Additional data were defined for collection. The collected data was analyzed and visualized providing an immediate feedback on students' performance. The visualization of results was displayed in the Apple's Game Center and has a form of achievements and leader boards. The achievements were visible by all students so as they could monitor their progress. However the implemented tool wasn't mentioned.

Empirical studies where learning analytics were integrated into SGs development are summarized in Table 4-5. The research showed that the implemented tool wasn't mentioned in the majority of the studies (5 out of 7). However the reviewed studies have a common approach in the development steps of SGs, all had as a basic principle to link educational goals with game design. The six developed SGs aimed to improve students' progress. Five of the studies pinpointed that learning analytics provide game improvement, monitoring of the class, prove game effectiveness, optimize curricula in educational settings, provide assessment feedback and have impact in classroom. Three of the studies differentiate students' learning process by gender. Only one study used existed SGs log files of VIBOA games to apply off-line posterior analysis.

Table 4-5: Empirical Studies for incorporating LA in SGs

Implemented Tool		
Unknown	(5 studies)	Malliarakis et al., 2014 Tlili et al., 2015 A. Serrano-Laguna & Fernandez-Manjon, 2014 Ali et al., 2017 Cariaga & Feria, 2015
ad-hoc mathmatical model	(1 study)	Malliarakis et al., 2015
SPSS (software for advanced statistical analysis)	(2 studies)	Tlili et al., 2015 Hauge et al., 2015
EngAGe (Engine for Assessment in Games)	(1 study)	Chaudy et al., 2014
DSL (Domain-Specific Language)	(1 study)	Chaudy et al., 2015
Web services	(1 study)	Chaudy et al., 2016
Xtext (an Eclipse tool to parse DSL)	(1 study)	Chaudy et al., 2017
GLEANER framework (LAM &LAS)	(1 study)	Hauge et al., 2014
EMERGO SG engine	(1 study)	Hauge et al., 2015
Developed SG		
CMX (Computer programming)	(1 study)	Malliarakis et al., 2014
CAG (Computer Architecture Game)	(1 study)	Tlili et al., 2015
Pilot study (SG GeoFall)	(1 study)	Chaudy et al., 2014
Lost in Space <XML> game	(1 study)	A. Serrano-Laguna & Fernandez-Manjon, 2014
Grab the Drink (cross platform SG)	(1 study)	Ali et al., 2017

Kinespell (SG for learning spelling)	(1 study)	Cariaga & Feria, 2015
Propreties/Attributes of developed SG revealed by LA application		
game design improvement/cofigurable game environment (based on feedback and performancies)	(5 studies)	Malliarakis et al., 2014 Tlili et al., 2015 Chaudy et al., 2014 Hauge et al., 2014 Cariaga & Feria, 2015
optimize curricula	(5 studies)	Malliarakis et al., 2015 Tlili et al., 2015 Chaudy et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014 Cariaga & Feria, 2015
enhance students' progress	(6 studies)	Malliarakis et al., 2016 Tlili et al., 2015 Chaudy et al., 2014 Hauge et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014 Cariaga & Feria, 2015
infer conclusion for assisting teaching	(4 studies)	Malliarakis et al., 2017 Tlili et al., 2015 Chaudy et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014
overall monitoring of students	(5 studies)	Malliarakis et al., 2018 Tlili et al., 2015 Chaudy et al., 2014 Hauge et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014
link educational goals and game design	(7 studies)	Malliarakis et al., 2018 Tlili et al., 2015 Chaudy et al., 2014 Hauge et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014 Ali et al., 2017 Cariaga & Feria, 2015
game effectiveness	(5 studies)	Malliarakis et al., 2019 Tlili et al., 2015 Chaudy et al., 2016 Hauge et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014
gender differentiation in learning process	(3 studies)	Tlili et al., 2015 Chaudy et al., 2014 Ali et al., 2017
rewarding system for players	(1 study)	Tlili et al., 2015
impact in classroom	(4 studies)	Malliarakis et al., 2019 Tlili et al., 2015 Chaudy et al., 2014 A. Serrano-Laguna & Fernandez-Manjon, 2014

5 Conclusions

5.1 Summary of the thesis

The digital evolution and extended use of internet lead to the rapid increase in the number of games' players. The success of entertainment games arouses interest of researchers in many educational domains. The traditional educational methods seem insufficient for the digital natives. Moreover the curricula enhancement with SGs leads to more interactive and engaging methods of delivering knowledge. Students learn as they play and play as they learn, and that facilitates the knowledge transmission in a disruptive way. However, SGs confront difficulties when applied in educational settings; teachers need to know how students interact with game, how the learning process occurs, and whether the desired learning outcomes are obtained. To overcome this issues LA must comprise an integral part of SGs. Teachers need to be provided with clear, simple and understandable methods so as to use SGs as educational and assessment tools. Though LA contributes to the adaptation of SGs there is a lack of standardized methods of integrating LA in SGs. Usually, ad-hoc solutions are provided, increasing the effort, cost, and time of the SGs development.

This thesis reviewed the current state of LA in SGs. SGs and LA definitions and current uses were illustrated. Learning analytics methods found in the literature were described. Game Analytics and Game learning Analytics differentiation and similarities in the implemented techniques were presented. LA steps and methodologies for incorporating LA in SGs performed thoroughly, from capturing in-game data traces to results visualization. The GLA architecture of the bibliography was presented analytically. The RAGE project technical application of tracking, real-time analysis and visualization tools were exhibited.

A quantitative and qualitative analysis was conducted according to Kitchenham's methodology for systematic literature reviews.

The thesis reviewed applied methodologies of patterns behavioral identifications. The primary aim of the research question was to study whether the application of LA in SGs could infer to patterns identification which will contribute to the establishment of an expert performance baseline so as to predict learning outcomes. Research on techniques and methods for predicting learning outcomes, shows that behavioral patterns are correlated with learning outcomes. The differentiations of expert-novice performance including behavioral profiling contribute to the establishment of an expert's baseline and with the comparison and classification techniques reveal distinction between patterns and finally, lead to the prediction of learning outcomes. Cluster analysis, correlation analysis, game telemetry and other techniques were used in the reviewed studies for patterns identification.

However, the scope of data collection reasons varies and shall be defined in an early stage of the game design so as to facilitate measurements in knowledge, behaviors, attitudes, and individual progress changes for comparing and contrasting performances and outcomes. In order to discover whether learning is obtained, learning signs have to be collected. The prediction model shall reveal future learners' performance and knowledge based on learners' present actions and achievements. Therefore to predict learning outcomes it is essential to build the learner's profile. SGs are perfect environments for behavioral identification patterns and with LA techniques marvelous outcomes may be achieved.

The GA techniques were studied and conclusions were inferred whether GA could be useful for SGs learning analytics. GA and SGA both aim to maximize the value of player data but SGA has additional purposes of performance estimation, evaluation, and improvement. GA methods and practices may contribute to the serious game learning analytics. Game industry uses telemetry methods for non-intrusive interaction data collection for various objectives from income prediction to the engagement measurement. The analysis of the collected data with data mining techniques reveals valuable insight of the game which aims to improve game design, increase game's expansion, and raise the revenue. Commercial games companies use posterior logging analysis to evaluate players' choices, to track in-game bottleneck, to make prediction for players' in-game actions, and this type of analysis can be applied in SG so as to establish connection between gaming and pedagogy. Common goals of GA and SGA are: players' preferences assessment, engagement and retention measurement, performance assessment, game design improvement, maximizing the value of player data. The common techniques that were found in bibliography are: data mining, posterior logging analysis, metrics associating game and players, telemetry for tracking interaction data.

This thesis is called to answer whether there are defined methodologies for implementing LA in SGs. Despite the adoption of serious games in educational environments there is still a lack of a general standardized approach for implementing learning analytics in SGs. A simple and transparent methodology of the SGs' full life cycle from early development stages to the final use, is necessary so as to simplify SGs acceptance. Unfortunately, nowadays game learning analytics usually is implemented for each case individually through ad-hoc solutions. In order to achieve a proper LA design in SGs a number of steps must be followed. The most critical is to define clear and realistic learning goals that should be included in game and learning design as it will inform us if the learning actually occurs. The majority of the studies defined clearly that educational goals shall be met with game design as well as the fact that the definition of learning goals is the first step of the process. Game mechanics, structure, objectives, game characters, learning objectives by means of variables must be included. The right definition of learning elements is critical as the learning evaluation outcomes depend on these variables. Defining variables and objectives ensure the collection of the right data. The next step is to define how the interacted data will be traced and collected, where the traces will be stored and if they will proceed for real-time analysis. Most studies performed the embedded tracker component in SGs for capturing and sending players' interaction data to the collector. The available interaction data may be stored for later analysis or may proceed for real-time analysis. Afterwards the visualization results may be reached by different stakeholders. LA in SGs provide evaluation to the design stage through feedback and improvement actions that can be reestablished in the system for learning and game design iterations. Students' assessment is also achievable in this stage with the visualization results. Most of the studies used standardized xAPI statements for the traces format and analytics platform developed for RAGE project. Game-independent analysis which is the default analysis and game-dependent which is a custom analysis are provided by the analytics system. Real-time analysis and visualization were necessary for displaying metrics to different stakeholders for various reasons. Some of the benefits of LA in SGs are: improvement and validation of SGs' development, SGs' effectiveness, insight and optimization of learning process, learning assessment, prediction of learning outcomes, monitoring and intervention in the classroom, personalized and adaptive player's experience.

The thesis included the review of empirical studies for integrating LA in SGS. The research showed that the implemented tool hasn't been mentioned in the majority of the studies. Two studies used SPSS software for statistical analysis. Some of the studies presented a framework for integrating LA in SG and case studies for the application of the proposed models. However the reviewed studies have a common approach in the development steps of SGs, while all had a basic principle to link educational goals with game design. Most of the developed SGs aimed to improve students' progress. The studies pinpointed that learning analytics provide game improvement, monitoring of the class, prove game effectiveness, optimize curricula in educational settings, provide assessment feedback and have impact in classroom. Several studies differentiate students' learning process by gender. Three of the SGs were developed for computer science education. Although, the reviewed studies implemented SGs with LA, a standardized method widely adapted for LA integration in SGs wasn't obvious.

5.2 Limitation of the study

Although, many studies were found where SGs were used in educational contexts, few presented tools for the implementation and integration of LA in SGs. The majority of the studies concentrate on a theoretical approach of LA in SGs. In the studies reviewed, we didn't find a widely adopted approach of integrating LA in SGs. Moreover, studies that use SGs as assessment tools for student's evaluation and student's acquired knowledge were limited.

The evaluation of the proposed solution for integrating LA in SGs, the proposed frameworks and methodologies were based only on the study of the selected bibliography. None of the proposed solutions were applied in order to empirically evaluate them.

Moreover, the selection of the studies was limited by the written language. All the studies that were included were written in English.

Finally, some of the studies that seem relevant for the thesis couldn't be reached due to access restrictions.

5.3 Future Work

The current thesis could be expanded in reviewing how easily an educator could use SGs incorporating LA with meeting two limitations: he/she isn't a computer science teacher and isn't acquainted with statistical analysis. Which of the tools and methodologies found in the thesis are more suitable and easy to use? Are there automated methodologies for the process?

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