# Supporting learning experience using technology-scaffolded methods

# *Abstract*

*The challenge of delivering personalized learning experiences is often increased depending on the size of classrooms and online learning communities. Serious Games (SGs) are more and more recognized for their potential to improve education. However, the issues related to their development and their level of effectiveness can be seriously affected when brought too rapidly in servicing growing online learning communities. Research is therefore needed not only to gain a deeper insight into how the students are playing, but also to deliver a comprehensive and intelligent learning framework that facilitates better understanding of learners' knowledge, effective assessment of their progress and continuous evaluation and optimization of the environments in which they learn. In line with the findings arising from the Horizon 2013 report, this paper aims to explore the potential in the use of games and learning analytics towards scaffolding and supporting teaching and learning experience. The conceptual model (ecosystem and architecture) discussed in this paper aims to highlight the key considerations that may advance the current state of learning analytics, adaptive learning and SGs, by leveraging SGs as an suitable medium for gathering data and performing adaptations. This paper includes existing findings and initiatives to support these considerations, which have the potential to affect the design and deployment of education and training in the future.*

**Introduction**

The EU Education and Training 2020 [1][[1]](#footnote-1) identified that a major challenge for improving the quality and efficiency of formal education (K12) is to ensure the acquisition of 21st century skills as means of developing excellence for allowing Europe to retain a strong global role. The 21st century is perceived as the beginning of a digital age with an unprecedented growth in technology, which offers unprecedented opportunities to improve quality, access and equity in education and training. There is also an emergence of new ways of learning characterized by personalization, engagement, use of digital media, collaboration, bottom-up practices and learner/teacher as a creator of the learning content. To effectively support the acquisition of 21st century skills, both teachers and students need to receive better and more personalized support in conjunction with effective deployment of technology-assisted approaches.

This is in line with a number of research studies and policy reports that have emerged over the past decade [2, 3, 4, 5] that emphasize how students can apply knowledge rather than how much knowledge has been attained. This presents a challenge in effective tracking and analysis of the right parameters related to students’ progress other than just a grading system based on traditional methods, stressing more on how to monitor and assess quality of the learning process and experience, as well as exploiting innovative technology-enabled disciplines such as social learning analytics (e.g. [6]).

The quality and efficacy of a learning process is influenced by the quality of teaching, learning support and environment. How can learners’ needs and performance be effectively monitored and exploited so that the right support is provided? Considered to be one of the most effective approaches to instruction, the Vygotskian scaffolding concept [7, 8] can be adapted. This concept allows individual learners to be given tailored support during the learning process, personalized to their individual needs. Understanding how the different learning preferences influence how learners learn most efficiently [9, 10] is essential to maximizing the impact of a teaching and learning process.

The scaffolding support required may be different for each individual, and may depend on several factors such as motivation, prior knowledge, psycho-physiological needs, interest, and context. With respect to the need for personalized support, the growing number of learners (for example students/trainees in classes and on Continuing Professional Development (CPD)) presents a new challenge in terms of a more scalable and sustainable way of monitoring learners performances as well as teaching strategies and methods. Timely access to selected, actionable information gathered across diverse data sources is hence a key determinant for scaffolding success and personalizing the learner's experience in real-time.

Existing and emerging trends, such as the increased use of Learning Management Systems (LMS), the deployment of online courses on a large scale (Massive Open Online Courses or MOOCs) and the ability of a game-based platform to engage large numbers of players for long periods of time provides an opportunity for a real wealth of data about students and their learning to be collected and utilized towards personalizing effective learner support in real-time interactions. Early analytic techniques currently implemented in education include attention metadata [11]; social network analysis [12] and recommender systems [13]. In terms of adapting to user models, adaptive web systems incorporate user models to adapt the systems’ behavior to individual users [14]. Intelligent tutoring systems (e.g., [15]) aim to offer to students individualized practice, as well as the dynamic composition and delivery of personalized learning utilizing reusable learning objects.

Beyond these there are not many, if any, learning analytics tools as such that captures variations of data on the actual learning process a learner will go through. Learning analytics-specific approaches are still at their infancy [16]. One of the many challenges is therefore how to best capture and reason these big datasets and utilize the analysis to inform teaching approach for the individual learners and adapt to their experience, whether within a virtual learning environment or the actual physical classroom delivery/deployment.

With this perspective, this paper introduces a conceptual model (ecosystem and architecture) that can potentially support the scaffolding of teaching and learning experience within a formal setting. This paper explores four (4) key considerations/components- (i) learning analytics platform, (ii) in-game and stealth measures, (iii) user modelling, adaptive control and visual analytics, and (iv) map of pedagogical patterns to game mechanics, and the respective evidence towards supporting the scaffolding ecosystem and architecture. The existing work reported includes on-going studies carried out under the EU-Funded Games and Learning Alliance (GALA).

Towards this end, the following section discusses the related concepts followed by the section on the conceptual architecture and the existing initiatives supporting the 4 key components. The overview of the conceptual ecosystem as a context for large-scale deployment is also discussed. The last section concludes the paper with the future research and development requirements for implementing the system and architecture in practice.

**2 Related concepts**

The Learning Analytics discipline [17, 18] consolidates its impact within Technology Enhanced Learning (TEL) as a methodology to determine how data collected from learners can help to improve the many aspects of the educational process. Despite being a relatively new discipline research on Learning Analytics have shown promising benefits. Solutions such as LOCO-Analyst and SNAPP [18] focus on the interactions performed by the students within the LMS, whose contents are mainly based on static learning objects with low user interactivity such as documents, presentations or videos. However, there are other educational resources, such as simulations games that present a higher level of interactivity and engagement and, therefore, generate a higher and more varied amount of log data to be analyzed.

Before any useful educational data can be effectively collected and learning outcomes can be maximized, engagement with a learning process must be established first. [19] emphasized that if a learning tool cannot engage learners, then sourcing an adequate sample of engaged users with whom to assess learning outcomes becomes an impossible task. How can the existing infrastructure within an educational institution be expanded to allow data on learners to be collected in a more engaging manner compared to traditional methods?

To promote and sustain engagement with a learning tool, a game-based approach has the ability to tap into our natural desire to be entertained. The impact of such an approach can be maximised if it provides insight into the learning experience, the learning environment and the actual performance during game play. It is also crucial that engagement with game play must be established before effective learning experiences can be measured and achieved [20]. Technologies developed for serious/non-entertainment games have become increasingly popular capitalising on the engaging factor of the game mechanics. Games such as America’s Army or Code of Everand reach large numbers of players, engaging them for long periods of time. Not only does this make them attractive platform for learning and training, but such tools also provide an opportunity for essential educational data to be recorded, monitored and analyzed [6].

In line with this perspective, [21] has also placed emphasis on both game-based learning and learning analytics as the technologies to be adopted over the next two to three years, which presents an opportunity for the benefits of both technologies to be merged and exploited towards supporting the scaffolding aim.

**2.1 Serious Games (SGs) as a platform to engage and sustain participation**

Game technology is considered as 'the innovation catalyst of information technology'[22]. [22] emphasizes that the future competitiveness of the EU Video Games Software Industry capitalize on the fact that the majority of the population in the future will be digital natives. A survey by the International Software Federation of Europe (ISFE) revealed that 74% of those in the 16-19 age range considered themselves as gamers (n=3000), while 60% of those 20-24, 56% 25-29 and 38% 30-44 considered themselves to be regular players of games. The power of games to immerse and motivate [23, 24] and the capabilities of games to change perceptions and views [25, 26] have created a more positive approach to games and new game genres. More use of games in non-entertainment contexts such as learning and training [27] are transforming everyday lives and multiplayer and social games communities are changing social interactions, leading to greater capabilities for social learning, interactions and importantly more fun in everyday contexts [28].

Despite significant challenges for researchers in the SGs field, some important scientific and empirical studies have been undertaken and can therefore serve as benchmarks for establishing the scientific validity in terms of the efficacy of using games to motivate learning and achieve learning outcomes. For example, the first pragmatic controlled trial showed how game-based approaches were found to be more effective than traditional learning in triage training [29], which is used as part of a training programme. In another study, [30] showed how game-based approaches in Re-Mission could support medication adherence in children with cancer. The study by [26] on FloodSim likewise showed how awareness raising of flooding policy could be supported by game-based approaches. And recently, [31] demonstrated that a game-based learning platform, when deployed within a classroom setting, promotes knowledge transfer and encourage communal discourse on sensitive issues.

These evaluations do not include the specific analysis of the learners’ performance during the learning process (game play). However, these early studies have attempted to broaden the methods and evaluation approaches, for example allowing us to refine metrics and measures that can support learning more effectively and replicate effective game design processes. These early studies have collectively demonstrated that when comparing games with traditional learning there is a significant difference in favour of games (see [29, 31]). That proven, 'game science' as it is coming to be called is looking at new ways to map more closely against human experiences and big data and learning analytics are potential tools for allowing us to do this.

**2.2 The potential of learning analytics and big data**

Learning analytics is an emerging field of technology-enhanced learning and it is related with a number of associated research areas including big data, web analytics, educational data and recommender systems [32, 33]. The common denominator of all these related areas is that they explore ways of collecting large amount of detailed data in order to find, analyse and present different patterns [11]. One way of collecting such kind of data is through data mining processes and techniques that would allow recommendation mechanisms for learning activities, people, educational content and educational tools that are likely to have a meaningful purpose for the user. [34] emphasise the use of analytics in terms of measuring, improving and comparing the performance of individuals not just to enhance the experience but also to facilitate better performance and outcomes to the activity.

[35] argue that analytics tools provide statistical evaluation of rich data sources to discern patterns that can help individuals at educational institutions make more informed decisions. These decisions are derived through technical or statistical activities which can be perceived as the primary focus of analysis in analytics. A transition in analytics from a quantitative orientation to one that emphasises more qualitative processes closely reflecting sense making, conceptions of big data, variations of using analytics tools, action planning and decision making may help to increase interest among researchers and practitioners alike [16].

There are early analytic techniques that are currently being used in education such as attention metadata [11]; social network analysis [12] and recommender systems [13]. Beyond these there are not many, if any, learning analytics tools as such that captures variations of data on what students do in order to learn. According to [16] this is mainly because learning analytics-specific approaches are at their infancy, thus more research is required. Increasingly, large data sets are available from students’ engagement with technology-enhanced learning encompassing the use of educational software and the amalgamation of educational authoring tools with Virtual Learning Environments (VLEs) or Management Learning Systems (MLSs). [12] define learning analytics as the “measurement, collection, analysis and reporting of data about learners and their context, for purposes of understanding and optimising learning and the environments in which it occurs” p.3. The integration of learning analytics in LMSs contributed on managing the back office functionality that would provide feedback on students’ activities on the system. An alternative way of referring to learning analytics is academic analytics [36].

This system-generated data would aid educationalists on identifying student’s learning problems or concerns and thereby offering a customised learning experience. [37] argued that the analysis of this data would not only approached from a quantitative perspective, but would also need a qualitative analysis for understanding conceptions, beliefs and actions of learning instances and associate them with the teaching practice. This would include a realistic and valued interpretation of both efficient and inefficient experiences of the environment and offering suggestions for progressing from the one end to the other. [38] argue that learning analytics may provide useful information not only for improving andlearning, but also for providing learners with recommendations in their learning based on previous learning activity orchestrations. This would enable students to receive learning-oriented material and feedback tailored to their own needs, abilities and learning characteristics. This would offer a change in the realm of learning analytics because it would offer not only academic management but also would provide computer-generated suggestions on learning content that is directly related to student’s preferences and needs.

This will set the ground for exploratory research on how learning analytics support personalised learning experiences through customized recommendations. The accuracy of such recommendations should be carefully considered possibly through integrating data from multiple sources for improving the accuracy of a student profile and subsequent personalisation of content. Therefore the inclusion of data from other sources such as mobile devices, physical data from supervision meetings and game environments in conjunction with the use of university resources such as libraries as well as learners’ preferences might result in a more complete learner profile.

**2.3 Learning Analytics for SGs**

The increasing acceptance of SGs leads to teachers from different areas and levels to use games (or game-like activities) to engage their students [39] SGs allow students to be presented with new situations and challenges related to complex skills that differ from the typical lecture/exam contents. However, most of these activities seldom contribute to the final student evaluation because most games and simulations lack an appropriate assessment system to generate rigorous and reliable student results. Therefore, while games promise to teach in innovative ways, the assessment of their effectiveness tends to gravitate back to written examinations or debriefing sessions [40, 41] This has caused an increasing gap between the purportedly deep learning that can be conveyed by educational games and the shallow techniques that are used to assess learners’ performance at present.

Different solutions and techniques have been proposed to fill this gap, including using the games themselves to assess the performance. Intrinsic techniques leverage the game technology itself to create in-game assessment tools, either explicit (asking in-game questions, having the player perform a specific evaluated task, etc) or implicit (producing a grade through indirect measurement of performance). The field of implicit in-game evaluation (also called stealth assessment [42]) offers rich opportunities: since games are highly interactive and complex software artefacts, they can produce a great amount of data on how the user is playing, which is readily available for assessment purposes. However, the best methods and techniques for utilizing all this data to measure learning effectiveness and assessing learners most effectively remains an open research and development challenge.

According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and complex relations between these concepts and experiences. This kind of modelling makes it possible to reproduce conceptual learning processes and thus uncover the frequencies, dependencies and patterns behind the conceptual change and learning transfer. When adding a Big Data dimension, the national level learning challenges can be uncovered and national curriculum designers will benefit from important real-time information [43]. It is therefore useful to scope the current applications and refinements of Learning Analytics techniques, adapting them to the specific context of SGs in order to leverage the vast amount of trace data that games can generate to provide rich learner-based assessment information. The following sections 3 and 4 discuss a conceptual model for optimizing the use of Learning Analytics and SGs towards supporting the dynamic nature of teaching and learning processes.

**3. The conceptual architecture**

In order to analyse learning within a game environment, the analytics platform needs to take into considerations the use of stealth and in-game measures influenced by the pedagogical perspectives of the intended game play towards understanding the learners and providing personalised feedback and support to them. With this perspective, a general architecture and the considerations based on existing work in the area is discussed in this section. The discussion includes existing and on-going studies supporting the components highlighted in fig. 1 (b), which will support the iterative analytic process illustrated in fig. 1(a).



**(a) (b)**

Fig. 1. (a) The iterative and continuous process of monitoring and analysing data based on the metrics and KPIs specific to the stakeholders, supported by (b) the key technical components to support a pedagogically-driven learning analytics and adaptive platform

It is important to understand learners’ preferences to allow learning and playing patterns to be analyzed and adapted. Adaptivity to different learning preferences and needs requires conceptualizing the user in terms of their learning capabilities and learning progress by investigating what parameters would most accurately characterize the learners - and how do these map to specific learner categories.

Capturing learners’ activity during game play can help measure these parameters. However, meaningful interaction and engagement from a learning perspective need to be defined and, correctly and ethically captured (using opt in and opt out user consent) during game-play. To support such measurement, in-game measures have to be based on the theoretical construct structured by the pedagogical patterns related to game design patterns, which provides the relationship between game and learning contents. This provides a more effective way to data mine relevant data, extract meaningful learning interactions and gain insight on how learning can be scaffolded. Analysis from this real-time data can be used to build the relevant user models, which could be included in the feedback, reporting and adaption process. The visualization of the analyzed data is also important to maximize the benefits of the correlated and fused information about the learners.

The potential impact of such system is to allow continuous monitoring and support, where the immediate outcomes (feedback, report, learner models) can be subsequently validated by (i) iteratively adapting a game environment to match the individual learners’ model and track the performance continuously, and (ii) evaluating the resulting intervention within a classroom setting, where teachers will be able to design their teaching strategy based on the analysis and insights.

The following sections further elaborate on these 4 components (fig. 2b) and the relevant studies that influence the ecosystem and the architecture of the proposed model.

**3.1 Learning Analytics Platform: Understanding learners/players using a SGs-tailored learning analytics approach**

The goal of learning analytics includes enabling teachers and schools to tailor educational opportunities to each student’s level of need and ability. Learning Analytics addresses and expands on the application of known methods and models to understand student learning and organizational learning systems. Unlike educational data mining, which emphasizes system-generated and automated responses to students, Learning Analytics enables human tailoring of responses, such as through adapting instructional content, intervening with at-risk students, and providing feedback [44]. With this perspective, existing tools, such as the Games and LEarning ANalytics for Educational Research (GLEANER, see fig. 2) has been implemented to support the tracking of learners and analyze their in-game activities. Gleaner, developed as part of the R&D activity under the EU-Funded Games and Learning Alliance (GALA) network, both an abstract framework and an implementation to support the Learning Analytics approach applied to educational videogames [45].

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Fig. 2. Main components of GLEANER, and their relationship with the game engine- from capturing and measuring data to reporting the analysis and adapting the existing environment to respond.

GLEANER is composed of a Learning Analytics Model (LAM) that defines all the information required for every step, and a Learning Analytics System (LAS) comprises all the processing power required by the model (see Fig. 3). The LAS component is created as a service, that can be remotely located, and which collects the traces generated by the game. The game pushes information to the server according to a specific API, and the instructors can also access the server separately to follow the updates. The implementation of the service and the communication is structured around the following steps:

1. The game engine reports user interactions to the capturer module, filtering data according to the selection model.
2. The aggregator filters the received data and may aggregate and transform sets of low-level traces into higher lever traces according to the aggregation model. This allows the instructor to extract meaningful information of the student actions, based analysis of the students’ game-play interactions that can be used in the later phases of the analysis.
3. The reporter module presents data and statistics in an human-friendly visualization, according to the instructions in the reporter model. This allows the instructor to get a summary of the students’ performance levels at a glance, at individual student’s level or at Course Level. This may also be used to allow students to compare their progress with their peers
4. The evaluator module can perform automatic assessment of the learning experience, checking the collected traces against a list of learning goals as described in the evaluation model. The objective is to predict the knowledge gain (or potential lack of).
5. The adapter module can use the information reported by the previous module to trigger changes in the state of the game, according to an *adaptation model*.
6. These technical modules, along with their driving abstract models, are the base for the scaffolded approach presented in this work.

**3.2 Stealth and in-game measures: Capturing meaningful interactions**

Meaningful interactions within the game are indeed the core of a learning experience. Meaningful in this case refers to interaction and engagement with contents that result in learning. This suggests an alternative approach to assessment based on tracking and analyzing the interactions during the learning experience, rather than using a separate instrument. The engagement with the learning content can be tracked using in-game measurement identifying the exploratory path taken during game-play and the specific content accessed by the players. Recorded information can be the number of times tutorials and hints are accessed, the amount of time spent on problem-solving mini games, the scores based on problems solved.

Based on the on-going studies on the GLEANER framework [46], we identify that it is essential to establish which generic and specific data must be captured for an effective evaluation of educational games, depend on the individual characteristics of each simulation and game (field, scope, interaction mode, deployment device) and have a more general nature. The study of the types of in-game traces that may be used when applying Learning Analytics techniques to SGs was based on literature reviews and game analyses, and three main types of traces are identified.

**Generic traces** are those that may be gathered from any SGs, regardless of the specific type. Given the enormous variety of SGs, there are few such possible traces. In particular, we identified two main subtypes: Low-level device events (e.g. mouse clicks or key presses) and State-change events (e.g. an in-game variable changes its current value, which may move the game forward). Using generic traces is a relatively straightforward process, and the GLEANER framework provides an API that any third-party game engine could use [47].

However, the expressive power of such traces is limited by their generic nature. In the other extreme, we can define **game-level traces**, designed to track specific in-game actions relevant in a particular game design. Such traces can convey more information than generic traces, and be more useful both for assessment and evaluation. Such traces will require automatic means of analysis and reasoning for game-specific traces and this will imply that the application has to be scaled with respect to specific metrics and KPIs.

As a balance, **genre-level traces** offer a middle ground, allowing the effort to focus on specific traces that can be applied across a variety of games. An example would be the implementation of GLEANER on the eAdventure game platform [47]. In addition to generic traces, this implementation adds support for additional types of traces that can be then applied to any game created with the eAdventure platform.

The definition of game-specific (or genre-specific traces) is the key to understanding how the students are interacting with the game. However, defining and supporting such traces requires the modification intervention in all the models and technical modules described in the previous section. The key is thus to focus on a) facilitating the modification process for the modules and abstract models and b) focusing on genre-level traces as this would protect the investment by being applicable to different future games.

**3.3 Mapping pedagogical patterns to game mechanics: Theoretical constructs to game and learning interaction**

Tracking learner interaction during game play provides vital information that will allow different learning styles and conceptions of, and approaches to teaching using technology (see for example [48] to be analyzed as well as game play and content to be adapted. As described above, this operation is performed in GLEANER through the definition of a report model and an evaluation model that drive the transformation of the raw tracking data into reports and assessments. However, configuring these models to provide good insights into the learning process, requires a deep understanding of how learning happens when the user interacts with the game.

The reasoning of in-game interactions pertaining to learning has to be pedagogically driven by extracting the relationship between games and learning mechanics at the abstract and concrete level- the fundamentals behind what links a game design pattern to a pedagogical pattern. The Learning-Game Mechanics mapping (LM-GM) framework [49] part of development under the GALA network, provides a basis to construct use-case models which has been validated using two comparative user tests demonstrating the advantages of the proposed model with respect to a similar state-of-the-art framework [50]. This mapping has also been used by [] to validate the relationship between the learning mechanics and game mechanics implemented in the PREPARe game, which has undergone a cluster randomized control trial that concluded positive learning outcomes.

The LM-GM was originally designed as a regression tool used in the development of SGs [51]. The intention was to provide SG developers a means of identifying the influence of gaming mechanisms to mechanisms of some pedagogical practice attributed with the game. Pedagogical elements are considered abstract interfaces while game elements are deemed as a concrete interface of SGs. This provides a clear relationship definition for the LAM in fig. 3 to track and process data. The LM-GM mapping visualises the configuration and flow of the game-based learning application and so allows quick identification of key engagement points in the game play. Based on similar principles, the LAM would be able to ascertain meaningful learning engagement during game play to be correctly tracked and assessed.

Mapping learning mechanics to game mechanics is crucial in order to inform the definition of in-game measures and to keep the balance in adaptation process. Previous studies [51, 52] have shown that without having a balancing mechanism between learning process and adaptation mechanisms, there will be uncertainty within the framework. Finally, no optimisation is possible without mapping the real world learning process against artificial learning or game mechanics. In playing a game, learners exhibit, through their gaming activities and the choices they make, preferential interaction modes. However, the way they play and their preferences in terms of game-play are determined to a large extent by the game rules and game mechanics. As with education the associated outcome of games can be considered generic, i.e. the aim is to acquire knowledge, skills and attitude. Insofar, it is about the value of practical experience and the appreciation of developing personal and technical skills alongside knowledge. For this reason, understanding the motivations of the learner in SG games and their relationship towards pedagogical outcomes and the gaming experience is important to the scaffolding paradigm.

**3.4 User modelling, adaptive control and visual analytics: Providing personalization**

The importance of engaging learners’ for achieving successful learning has already been pointed out and it has been argued that stealth assessment and flow analysis can be exploited to adapt game content for keeping learners’ engaged. Moreover, the crucial importance of understanding mappings between game mechanics and learning mechanisms for achieving successful learning has been pointed out. Although these components are essential there is another dimension too: individuality of learners. Individual learners’ may have varying preferences with respect to engaging game play and game mechanics, they may respond differently to varying strategies for learning, they may have varying requirements with respect to cognitive aspects, and they may have varying prior knowledge; their requirements with respect to optimal learning varies. It is thus essential to understand the specific needs of individual learners’ and to understand the relationship between preferences and content, in order to properly adapt and control game content to provide a more personalized experience. Adaptive web systems have investigated a range of approaches to user profiling. The most popular features modeled and used by adaptive web systems are user knowledge, interests, goals, background, individual traits, and context of work, while each individual adaptive system typically focuses on some of these factors [14].

User modelling refers to, in the context of games and learning, a process where multiple users are analysed to distinguish categorizations of learners’ with respect to e.g. learning behaviours, game play interaction, preference, content, which can be used for optimizing the learning process. More specifically, user models abstract the distinctive features of a user, so that it can be continuously updated by the game-based environment while giving input to a personalization engine, which adapts the contents and their provision modalities to the elicited requirements. Mathematics Navigator [53] for instance, applies Teachable Agents in recording and analyzing learners’ knowledge and then optimizing the future learning path to override the difficulties in learning. Teachable Agents can also be used to decrease Information Overload [54] and so adapt the content to the learner's needs. User modelling methods have been widely used in the context of Intelligent Tutoring Systems, Adaptive Hypermedia Systems, which can be adapted to support user modelling in games for learning in conjunction with the GLEANER framework (fig. 3). In particular, the aggregated and refined outputs of the evaluator module are potentially a useful starting point for adaptation decisions inside the game.

The proposed ecosystem needs to engage and support stakeholders, teachers, students, school administrators and regional and state bodies by exploiting and analysing large datasets. In order to provide interactive, personalized and immersive interfaces to deal with this data, as well as allowing a continuous adaptation of the process by the teachers, visual analytics (VA) can be used as a design framework. VA is defined as analytical reasoning supported by highly interactive visual interfaces [55] and it strives to facilitate the analytical reasoning process by creating software that maximizes the human capacity to perceive, understand, and learn from large, complex and dynamic data and situations. Establishing the analytical reasoning process that needs to be supported for the different actors involved in the ecosystem proposed is essential to successfully develop the activities described by GLEANER, especially the reporter module and abstract model, that provides on one hand a set of predefined but customizable reporting views, but also provides extension points to add new modules to provide tailored views. VA advocates for the design of transparent user modelling and adaptation modules, guided in our case, by the teachers. Moreover, it is important to provide a user-friendly infrastructure - personalized dashboards to provide feedback, summaries, actionable steps, visualizations of the learning processes, statistics about the examination outcomes, etc. The system allows key players, such as the teachers and administrators, to be involved in the adaptation of the content based on the analysis of the learners’ progress.

The use of VA and its benefits to support e-learning has recently been suggested by, for example [56]. Even if the application of VA principles to e-learning is considerably new, there are several examples in the literature that show the advantages of using interactive visual environments for learning through, for example, graphic organizers, such as mind or conceptual maps, or more advanced tools that permit the visual management of e-learning contents, e.g. Classroom BRIDGE, ENCCON, TM4L, etc. (see a more extensive review in [56]). Visualization can be also used to represent the learning process, its dynamics and interactions between students and groups. An example of the latter is CourseVis, presented in [57], where several 2D and 3D visualizations are provided for helping the instructors to form a mental model of their class and provide appropriate help.

**4. The conceptual ecosystem: Towards a large-scale deployment**

Within a larger-scale perspective, such architecture could potentially support and benefit an ecosystem of learners, teachers, administrators, learning designers and game developers, where valuable analysis of learners within an educational context will guide teaching and learning strategy, resource management, adaptive game-based learning design and learning content development. Figure 3 illustrates an ecosystem aiming to support the capturing and reasoning of large-scale educational data from engaging sources to better understand learners' knowledge, assess their progress and provide actionable feedback, which will be relevant to the stakeholders involved.

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Fig. 3. A conceptual ecosystem

Participatory approach is of key importance to the teaching and learning ecosystem, where the metrics and performance indicators specific to the stakeholders can be specified and included in the design of the intelligent learning environment.

Non-scientific users, such as learners, teachers, parents, school administrators and state/regional bodies, could be offered support and they will be able to engage with and exploit large datasets. Learners and teachers/instructors will obtain a better perspective of the educational process and its results based on the specific course/module, which will help individual learners to reach their learning goals and the teachers/instructors to provide the right support to their pupils/trainees. For example, MathElements, a game targeting an ecosystem of pre-school children, teachers and parents utilises on learning analytics [54] that provide insights on learner's strengths and weaknesses in order to support teacher and/or parent in instructing the learner. The Monster Manor game is a part of a “playful” and “incentivized” ecosystem involving parents and clinicians aiming to motivate children with Type 1 Diabetes to check their blood sugar regularly [31]. Parents are able to monitor their child’s progress and encourage positive and healthy behaviour. The sustainability game helps students to raise awareness on sustainability issues for public spaces [58]. Teachers are able to provide feedback while students are playing on different quests and try to steer learning in relation to intended learning outcomes.

Predictive models and success/failure patterns can be correlated in the analyzed data based on the specific measures and metrics, which can be used to design actionable solutions to overcome the weakness of the teaching and learning strategy and resource allocation on the institutional level. For example, [59] studied the relation between learning outcomes, speed of interaction and nature of misunderstandings. Based on these parameters, they have suggested a simple adaptation algorithm on predicting on optimal learning zone. By analysing individual learning processes, Math Elements also helps to identify topics on the curriculum that needs additional emphasis [59]. The ClassMATE framework [60] introduces a pervasive ecosystem that assists in a non-obstructive way the students during learning activities both at school and at home. ClassMATE supports collaborative tasks, application migration, service personalization and personalization of semantically discovered content to each individual learner’s needs. Its main advantage is that every decision made and action taken is driven by contextual information (who, when, where, what) towards facilitating end user interaction (student or teacher).

The scaffolding ecosystem could also potentially impact the administrative and policy levels in the long run, and benefits could include insights that will inform resources allocation and potentially change of instructional strategy. The ecosystem should also embrace adaptivity, where the game-based learning environment can be adapted to support specific learner profiling which will allow longitudinal studies on how learning experience evolve with time and with respect to the change of teaching and learning strategy to respond to the learners’ specific needs.

Bringing together SGs and Learning Analytics to facilitate the understanding and support of learners could offer an intelligent and interoperable learning framework capitalizing on learning analytics tools that can be implemented and integrated onto a LMS, a game engine or a game editor to provide a wide range of scaffolded support for learners and teachers/instructors within a formal setting. However, there are several challenges on recording big data on learning, privacy being one of the key issues. In terms of deployment within a formal setting, the context of deployment has to consider the existing infrastructure and the needs of the beneficiaries.

**5. Conclusions and future work**

ICT solutions are widely being deployed in schools, universities and training institutions, which include Learning Management Systems (LMSs), e-learning and game-based learning platforms. The efficient use of ICT should imply the use of less resources allowing for wide applicability and interoperability within the existing infrastructure. The ICT solution should also be user friendly and adaptive to maximize the use and scalability of the solution. And most importantly, the use of such solution should be evidence-based, where performance can be effectively monitored and personalization could be carried out to support the needs of the users.

ICT should not only be a platform for learning, but also to support strategic evaluation and monitoring of the needs of both learners and teachers/instructors. With the use of Learning Analytics, the proposed model aims to optimize ICT learning platforms and maximize usability and impact on the existing teaching and learning system. Learning Analytics emphasizes on the measurement and data collection as activities that educational organizations need to undertake and understand, focuses on the analysis and reporting of the data, which will subsequently allow actionable steps and measures to be designed to overcome potential issues or weaknesses. The use of a visual representation of analytics is critical to generate actionable analysis and information represented in an easily digestible form for decision makers. A statement such as “this person has done 70% of exercises and 80% of them correctly” gives an easily understandable measure. However, it is not detailed enough to provide informed judgements as to how well the exercise was conducted or how a solution was reached (and was that achieved through tractable means as opposed to a guess).

SCAFFOLD was inspired by the challenge to address how to best capture, analyse and present dynamic datasets and to utilize the analysis to predict the best teaching approach for the individual learners and adapt their experience, whether within a virtual learning environment or the actual physical delivery/deployment. The proposed model presents an opportunity for future evaluation of how the analytics and adaptation affects the learning experience by comparing the adapted learning experience with a control group using a default non-adapted version of the teaching and learning strategy or of the same serious game. The deployment evaluations will include empirical studies, such as cluster randomized control trials– with intervention and without intervention for both scenarios: game-based learning environment and the classroom teaching environment (pre and post surveys, questionnaires, analysis of in-game data, analysis of classroom performance, etc). Intervention in this case will be the scaffolded support based on the proposed model. In addition to experimental or quasi-experimental impact analysis, the evaluation could adopt a mixed method approach to explore changes in other important dimensions that may result from the engagement with the ecosystem, including but not limited to: (i) Changes in teaching practices, including changes in subject-specific and cross-curricular pedagogic approaches; (ii) Changes in patterns of homework/schoolwork among students, (iii) Changes in school-level approaches to curriculum design and implementation; and (iv) Changes in perceptions and attitudes among students in relation to interests and aspirations.

This opportunity will potentially affect the design and deployment of education and training in the future. The vast amount of data that is being collected about students also has policy implications in addition to technical ones. The investigation of how the collection and analysis of this educational data fits current institutional policies as well as European guidelines and ethical procedures can also be carried out. The availability of this type of data in different countries presents a unique opportunity. Not only will it be possible to investigate differences between countries and more accurately map and translate qualifications between countries, it will also have the potential to reveal differences between educational institutions and countries in terms of effectiveness.

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**References**

1. <http://europa.eu/legislation_summaries/education_training_youth/general_framework/ef0016_en.htm> [Accessed 2013 Sept 30]
2. Silva, E. (2009). Measuring Skills for 21st-Century learning. The Phi Delta Kappan. 90(9), 630-634.
3. Ananiadou & Claro. (2009). 21st Century Skills and Competencies for New Millennium Learners in OECD Countries. Available at: <http://www.oecd-ilibrary.org/education/21st-century-skills-and-competences-for-new-millennium-learners-in-oecd-countries_218525261154> [Last accessed 16 March 2013]
4. Dede, C. (2009). Comparing frameworks for 21st Century Skills. Available at: <http://dca1to1.pbworks.com/f/21st+Century+-+will+our+students+be+prepared.pdf> [Last Accessed 15 March 2013]
5. Eurydice (2012). Eurydice Report- Developing Key Competencies at School in Europe: Challenges and Opportunities for Policy. Available at: <http://eacea.ec.europa.eu/education/eurydice/documents/thematic_reports/145EN.pdf> [Last accessed 17 March 2013]
6. Buckingham Shum, S. & Ferguson, R. (2012). Social Learning Analytics. Educational Technology & Society 15(3), 3-26.
7. Vygotsky, L. S. (1978). Mind in society: The development of higher mental processes (M. Cole, V.John-Steiner, S. Scribner, & E. Soubeman, Eds.). Cambridge, MA Harvard University Press.
8. Wood, D., Brunet; J. & Ross, G. (1976). The role of tutoring in problem solving. Journal of Child Psychologyand Psychiatry and Allied Disciplines 17, 89-100.
9. Kolb, D.A. (1984). Experiential learning: Experience as the source of learning and development. Prentice-Hall Englewood Cliffs, NJ.
10. Coffield, F., Moseley, D., Hall, E & Ecclestone, K. (2004) Learning styles and pedagogy in post-16 learning: a systematic and critical review, LSRC reference, Learning & Skills Research Centre, London.
11. Duval. E. (2011). Learning Analytics for Visualisation and Recommendation, in Proceedings of LAK11: 1st International Conference on Learning Analytics and Knowledge.
12. Fournier, H., Kop, R, Hanan, S. (2011). The Value of Learning Analytics to Networked Learning on a Personal Learning Environment Available from: <http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/ctrl?action=rtdoc&an=18150452&lang=en> [Last accessed 8 September 2013]. Publications Archive Canada. Canada.
13. Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H. & Koper, R. (2011). Recommender Sysems in Technology Enhanced Learning, in Recommender Systems Handbook, F. Ricci, Rokach, L, Shapira, B, Kantor, P, Ed., ed: Springer, US, pp. 387-415.
14. Brusilovsky, P. and Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In: P. Brusilovsky, A. Kobsa and W. Neidl (eds.): The Adaptive Web: Methods and Strategies of Web Personalization. Lecture Notes in Computer Science, Vol. 4321, Berlin Heidelberg New York: Springer-Verlag, pp. 3-53.
15. Heilman, M., Collins-Thompson, K., Callan, J., Eskenazi, M. (2006). Classroom success of an Intelligent Tutoring System for lexical practice and reading comprehension. Proceedings of Interspeech 2006. Pittsburgh, U.S.A
16. Siemens, G. (2012). Learning Analytics: Envisioning a Research Discipline and a Domain of Practice, in Learning Analytics and Knowledge 2012, Vancouver, Canada.
17. Ali, L., Hatala, M., Gašević, D. & Jovanović, E. (2012). A qualitative evaluation of evolution of a learning analytics tool. Computers & Education 58(1), 470-489.
18. Dawson, S., Bakharia, A., & Heathcate, E. (2012). SNAPP: Realising the affordance of real-time SNA within networked learning. In proceedings of the 7th International Conference on Networked Learning, Aalborg, Denmark, pp. 125-133.
19. Sweetser P. & Wyeth P. (2005). GameFlow: A Model for Evaluating Player Enjoyment in Games. ACM Computers in Entertainment 3(3)
20. Whitton, N. (2011). Game Engagement Theory and Adult Learning. Simulation & Gaming 42(5), 596–609.

1. <http://www.nmc.org/pdf/2013-horizon-report-HE.pdf> [Accessed 1 October 2013]
2. JRC (2010). Born Digital/Grown Digital: Assessing the Future Competitiveness of the EU Video Games Software Industry, The JRC Scientific and Technical Report, EUR 24555 En-2010.
3. Garris, R., Ahlers, R. & Driskell, J. E. (2002). Games, Motivation, and Learning: A Research and Practice Model. Simulation and Gaming 33, 441-467.
4. Panzoli, D., Qureshi, A., Dunwell, I., Petridis, P., de Freitas, S. & Rebolledo-Mendez, G. (2010). Levels of Interaction (LoI): A Model for Scaffolding Learner Engagement in an Immersive Environment. Intelligent Tutoring Systems. Lecture Notes in Computer Science 6095, 393-395.
5. deFreitas, S. (2011). Game for Change. Nature 470 (7334), 330-331.
6. Rebolledo-Mendez, G., Avramides, K., de Freitas & S.. Memarzia, K. Societal impact of a Serious Game on raising public awareness: the case of FloodSim, In Proceedings of the 2009 ACM SIGGRAPH Symposium on Video Games. New Orleans, Louisiana. pp. 15-22.
7. Mautone, P.D., Spiker, V.A. & Karp, M.R. (2008). Using Serious Game Technology to Improve Aircrew Training. In proceedings of the Interservice/Industry Training, Simulation and Education Conference (IITSEC).
8. McGonigal, J. (2008). Reality is Broken: Why games make us better and how they can change the world. London. Jonathan Cape.
9. Knight, J., Carly, S., Tregunna, B., Jarvis, S., Smithies, R., de Freitas, S., Mackway-Jones, K. & Dunwell, I. (2010). Serious gaming technology in major incident triage training: A pragmatic controlled trial. Resuscitation Journal 81(9), 1174-9.
10. Kato, P. M., S. W. Cole, Bradlyn, A. S. & Pollock, B. H.. (2008). A Video game improves behavioural outcomes in adolescents and young adults with cancer: A randomized trial. Paediatrics 122(2), 305-317.
11. Arnab, S. (2013). Hobby to habits. Public Service Review: Health And Social Care 35, 105-105
12. Ferguson, R. (2012). The State Of Learning Analytics in 2012: A Review and Future Challenges. Technical Report KMI-12-01, Knowledge Media Institute, The Open University, UK.
13. Ferguson, R. (2012). Learning Analytics: Drivers, Developments and Challenges. International Journal of Technology Enhanced Learning 5, 304-317.
14. Norris, D., Baer, L, Offerman, M. (2010). A National Agenda for Action Analytics National Symposium on Action Analytics. Available from: <http://www.edu1world.org/PublicForumActionAnalytics/>  [Last accessed 6 Sept 2013].
15. EDUCAUSE Initiative (2010). 7 things you should know about ANALYTICS. Available from <http://www.educause.edu/library/resources/7-things-you-should-know-about-intelligent-tutoring-systems> [Last accessed 5 Sept 2013]
16. Dawson, S., Heathcote, L., & Poole, G. (2010). Harnessing ICT potential: The adaptation and analysis of ICT systems for enhancing the student learning experience. International Journal of Educational Management 24.
17. Downes, S. (2010). Dell Cloud Services: Collaboration, Analytics and the LMS: A Conversation with Stephen Downes , Available at: <http://campustechnology.com/newsletters/ctfocus/2010/10/collaboration_analytics_and-the-lms_a-conversation-with-stephen-downes.aspx2010>.[Last accessed 9 Sept 2013]
18. Kop, R. (2010). The Design and Development of a Personal Learning Environment: Researching the learning experience. Presented at the European Distance and E-Learning Network, Valencia, Spain.
19. Bourgonjon, J., De Grove, F., De Smet, C., Van Looy, J., Soetaert, R. & Valcke, M. (2013). Acceptance of game-based learning by secondary school teachers. Computers & Education 67, 21-35.
20. Peters, V. a. M. & Vissers, G. a. N. (2008). A Simple Classification Model for Debriefing Simulation Games. Simulation & Gaming 35(1), 70–84.
21. Arnab, S., Brown, K., Clarke, S., Dunwell, I., Lim, T., Suttie, N., Louchart, S., Hendrix, M. & de Freitas, S. (2013a). The Development Approach of a Pedagogically-Driven Serious Game to support Relationship and Sex Education (RSE) within a classroom setting. Computers & Education 69, 15-30.
22. Shute, V. J. (2011). Stealth Assessment in Computer-Based Games to Support Learning. In S. Tobias & J. D. Fletcher (Eds.), Computer Games and Instruction. Information Age Publishers, pp. 503–523.
23. Ketamo, H. & Kiili, K. (2010). Conceptual change takes time: Game based learning cannot be only supplementary amusement. Journal of Educational Multimedia and Hypermedia19(4), 399-419.
24. Bienkowski, M., Feng, M. & Means, B. (2012). Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics. An Issue Brief. U.S. Department of Education Office of Educational Technology.
25. Serrano-Laguna, Á., Marchiori E. J. et al. (2011). A framework to improve evaluation in educational games. In Proceedings Proceedings of the IEEE Engineering Education Conference (EDUCON), Marrakesh, Morocco
26. Moreno-Ger, P., Manjón, B. F, Laguna, A. S., Ortiz, I. M., Kiilli, K., Ninaus, M., Kober, S. E., Wood, G., Neuper, C., Berta, R., van Oostendorp, H., Wouters, P., Veltkamp, R., Arnab, S., Imiruaye, O., Dunwell, I. & Liarakopis, F. (2013). D2.3 Priority Area 1 Report, WP2 Research and Development, Games and Learning Alliance (GALA).
27. Serrano-Laguna, A. (2012). GLAS : a framework to improve assesment in educational videogames (Master Thesis). Universidad Complutense de Madrid. Obtained from UCM e-Prints: <http://eprints.ucm.es/16929/>
28. Lameras, P., Levy, P, Paraskakis, I, Webber, S (2012). "Blended university teaching using virtual learning environments: conceptions and approaches." Instructional Science 40(1): 141-157.
29. Lim, T., Louchart, S., Suttie, N., Ritchie, J., Aylett, R., Stanescu, I. A., Roceanu, I., Martinez-Ortiz, I., & Moreno-Ger, P. (2013). Strategies for Effective Digital Games Development and Implementation. In Y. Baek, & N. Whitton (Eds.), Cases on Digital Game-Based Learning: Methods, Models, and Strategies (pp. 168-198). Hershey, PA: Information Science Reference.
30. Arnab, S., Lim, T., Carvalho, M. B., Bellotti, F., de Freitas, S., Louchart S., Suttie, N., Berta R., De Gloria, A. (in press). Mapping Learning and Game Mechanics for Serious Games Analysis, British Journal of Educational Technology, to appear 2013.
31. Lim, T., Louchart, S. & Suttie, N. (2012). D2.2 TC2.1 Serious Games Mechanics Report, WP2 Research and Development, Games and Learning Alliance (GALA).
32. Ketamo, H. (2010). Balancing adaptive content with agents: Modeling and reproducing group behavior as computational system. In proceedings of 6th International Conference on Web Information Systems and Technologies, WEBIST 2010, Valencia, Spain, 1, pp. 291-296.
33. Ketamo, H., Alajääski, J. & Kiili, K. (2009). Self-Organizing Learning Material on Teacher Education. In Proceedings of EdMedia, Honolulu, Hawaii, pp. 3658-3667.
34. Ketamo, H. (2011a). Managing Information Overload - Teachable Media Agents. In Proceedings of the 8th International Conference on Intellectual Capital, Knowledge Management & Organisational Learning – ICICKM 2011. Bangkok, Thailand, pp. 301-308.
35. Thomas, J.J. & Cook, K.A. (2005). Illuminating the Path: The Research and Development Agenda for Visual Analytics. National Visualization and Analytics Ctr. IEEE Computer Society, Los Alametos, CA.
36. Gómez Aguilar, D. A., Suárez Guerrero, C., Therón, R. & García Peñalvo, F. (2010) Visual analytics to support e-learning In Ed. Mary Beth Rosson (pp. 207-228) IN-TECH: Advances in Learning Processes.
37. Mazza, R. & Dimitrova, V. (2005). Generation of graphical representations of student tracking data in course management systems. 9th International Conference on Information Visualisation, pp. 253-258.
38. Lameras, P., Petridis, P, Dunwell, I, Hendrix, M, Arnab, S, de Freitas, S, Stewart, C (2013). A Game-based Approach for Raising Awareness on Sustainability Issues in Public Spaces. The Spring Servitization Conference: Servitization in the multi-organisation enterprise 20-21 May 2013 Aston Business School Birmigham, UK.
39. Ketamo, H. (2011b). Sharing Behaviors in Games and Social Media. International Journal of Applied Mathematics and Informatics 5(1), 224-232.
40. Leonidis, A., Margetis, G., Antona, M., Stephanidis, C. (2010). ClassMATE: Enabling Ambient Intelligence in the Classroom. World Academy of Science, Engineering and Technology, 66, pp. 594 - 598.

1. <http://europa.eu/legislation_summaries/education_training_youth/general_framework/ef0016_en.htm> [Accessed 2013 Sept 30] [↑](#footnote-ref-1)