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Learning Analytics and Serious Games: Trends and Considerations

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ABSTRACT

This paper reviews the current status of Learning Analytics with special focus on their application in Serious Games. After presenting the advantages of incorporating Learning Analytics into game-based learning applications, different aspects regarding the integration process including modeling, tracing, aggregation, visualisation, analysis and employment of gameplay data are discussed. Associated challenges in this field as well as examples of best practices are also examined.

Categories and Subject Descriptors

K.8 [**Personal Computing**]: General—*Games*; K.3.1 [**Computers and Education**]: Computer Uses in Education; H.5.0 [**General**]: Human-Centered Computing

General Terms

Design, Measurement

Keywords

Learning Analytics, Serious Games, Game-Based Learning

1. INTRODUCTION

With the digital evolution in education comes a necessity for improving assessment strategies accordingly which are integral to any learning process. As educational data volumes increase and learning practices get more and more diverse, finding appropriate evaluation techniques becomes a challenging task. Although recent technological advances also enable advanced tools for gathering and analyzing data, research on how to best utilize this for enhancing learning and assessment in novel educational settings still has many open questions [7]. The emerging fields of Learning Analytics (LA) and Educational Data Mining (EDM) attempt to address these issues by exploring models and techniques for making efficient and effective use of educational data. This includes capturing, tracking, aggregating, analyzing, and visualizing/utilizing information about learners' interactions with learning content and their learning progress. Both disciplines have the common goal of using these traces to improve learning but their methodologies for exploring and using data are slightly different. While EDM is more concerned with analyzing and feeding data into automatic adaptation, prediction and recommendation algorithms, LA directs more emphasis to appropriately visualizing these mechanisms for the user (instructor, instructional designer, institution, parent and/or learner) and empowering him/her to interpret and intervene in the process [46].

Educators are increasingly recognizing the potential of using digital games to engage students in interactive and collaborative learning environments. Multimedia elements, storytelling, challenge, competition, random access, parallel processing, immediate reward and low level of threat are all features which make many people prefer them to traditional learning media [41]. In general, games that have a certain positive goal beside entertainment (education, health promotion, etc.) are referred to as *Serious Games*. Although this paper focuses on educational games, other types of Serious Games can also benefit from analytics, e.g. for assessing the engagement of players during the game. Making sure that a Serious Game reaches the goal which was set by the teacher/developer is not an easy task. Not only should engagement and usability of an educational game be tested to make sure people will use it long enough without getting bored or frustrated, the learning outcome should also be assessed. Even with careful design and heuristic evaluation some issues are only discovered in user studies incorporating realistic settings. However, to justify the expenses of using a Serious Game in a learning context, the game has to be evaluated and its benefit has to be proven. This is why developing good frameworks for the evaluation of Serious Games is a topic addressed by many researchers [19]. Here using LA is often seen to be a relatively objective and cost-effective evaluation approach compared to relying solely on self-reports and pre-/post-tests. It also has the ability to give real-time insight into possible shortcomings of an educational game. In addition to assessing games, the interactions

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of players during gameplay sessions can provide a lot of data which can be used for identifying user attributes, strengths and weaknesses. Due to their interactive and engaging nature, Serious Games can thus be designed in such a way that they can be used as effective measures of learner attributes and learning progress and might outperform traditional tests [18]. Here we are not only referring to games which explicitly employ quizzes as learning elements but rather games which have the evaluation mechanisms seamlessly integrated into their game mechanics. The term *Stealth Assessment* has been used to describe this approach [45]. Integrated into Serious Games, LA could thus perfectly fit as a tool providing implicit insight into a learner's knowledge state within the game. The big variety of educational games poses a significant challenge for defining a general methodology for integrating learning analytics into serious games in an effective way [44]. We will therefore in the next sections present several suggested solutions to this problem covering different aspects like modeling decisions, data collection, reduction, aggregation and analysis as well as effective use of results.

2. LEARNING ANALYTICS AND SERIOUS GAMES

To successfully assess learning using learning analytics, the learning domain, the application concept as well as the learner should be modelled in a way which facilitates data extraction and analysis. These models should preferably also be stored in separate files in an easy-to-process format [44]. In this regard existing models like the Competence-Based Knowledge Space Theory (CbKST) are usually used as a foundation [28, 17]. This theoretical framework requires learning domains to be modelled as a prerequisite competency structure to make the process of inferring knowledge states more efficient. Open Learner Model (OLM) [10] is becoming a popular term among LA researchers as it requires presenting to the learner an understandable visualization of his current knowledge state. Several studies have shown how the OLM approach improves learning outcomes [50, 35]. In some studies, the learner model was even made directly editable by learners. Using the *Mobile Open Leaner Model* the learner can also "carry" his learner model with him/her and exchange it with other students to facilitate peer tutoring [9]. Adaptive learning games, like adaptive tutoring systems, already need to employ a learner model for their adaptation mechanism. One suitable model for this kind of games which considers not only the knowledge state but also the player type and the narrative aspects of the game is the concept of Narrative Game-Based Learning Objects (NGLOB) [20]. Here the representation of context information consists of a triple vector for each scene containing information about the narrative context (how appropriate a scene is for which step in which story model), the gaming context (how appropriate a gaming situation is for which player type) as well as the learning context (all associated and prerequisite skills of a learning situation). Dependencies between skills are modeled as a graph based on the CbKST [28]. Before being able to apply such an approach, relevant information should exist and be appropriately structured to provide the following models: A Competency Model, an Evidence Model and a Task/Action Model [45]. The Competency Model should present a fine-grained specification of competencies which should be assessed. The Evidence model should relate different actions and behaviors of a player within a learning game to the different competencies. In this regard, Domain Structure Discovery refers to the problem of mapping tasks to knowledge components or skills [47]. Conceptualizing how a certain gaming context should be best designed so that player actions required will result in measurable inference about their competency level constitutes the Action Model. This approach in designing learning environments is referred to as Evidence-Centered Design (ECD) [34]. In addition to modelling learning, other aspects like engagement are worth modeling in the case of evaluating educational games.Therefore it is suggested to not only collect evidence on the player's state of knowledge using a so-called Skill Assessment Engine (SAE) but also considering his motivation level through a Motivation Assessment Engine (MAE) as well [24]. The process of integrating learning analytics into a learning application is composed of several tasks:

2.1 Choosing Data

Determining which information needs to be extracted is an essential step for using learning analytics. This depends not only on the learning goals, setting and tasks but also on the game genre, mechanic and platform.

2.1.1 Intensive vs. Extensive Data

One possible classification of data to be collected using learning analytics depends on whether quantity or quality is desired. Collecting data from a large number of users with only few information gathered about each user results in extensive data while focusing on a limited number of participants to make deeper and more-detailed observation produces intensive data [21]. Extensive data is primarily for Educational Data Mining where patterns are recognized across large data sets while intensive data performs better at recognizing patterns across multiple different data streams of one and the same user over time. In some cases an approach combining both intensive and extensive data may be best as both complement each other ensuring that no significant patterns are overlooked.

2.1.2 Single-Player vs. Multiplayer

Collecting data from multiplayer games poses its own challenges arising from the additional social component. Learners' interactions in a collaborative learning environment, within a Learning Management System (LMS) or a multiplayer Serious Game, are a rich source of data which can be exploited using LA. Data extracted from similar environments can be fed into a social network analysis process to identify aspects of collaborative learning through relations and structures [37]. A diagnostic tool is presented in [27], where social networking principles are used for in-class peer assessment offering teachers a teacher supervision panel allowing monitoring task solutions and filtering collected information according to their diagnostic or instructional interest.

2.1.3 Generic vs. Game-Specific Traces

In [44] the authors define a set of generic traces which can be extracted within learning game experiences for learning analytics. The set consists of game traces (starting, quitting and ending a game), phase traces (starting and ending phases), meaningful variable traces (update of variables) and input traces (clicks and key presses). The *Game Start* trace not only contains information about the time the game was started but also basic information identifying the user and describing context and demography through technical data. The *Game End* trace records when the game was finished and, if the game has many endings, which ending was reached. If the game is quit before reaching the end, the *Game Quit* captures the context in which the session was interrupted. Phase changes can also be mapped to storytelling elements and are linked to sub-games or learning chapters in a game. Here, the *Phase Start* and *Phase End* traces can be used to identify when a phase has started/ended and whether or not it was completed with success. Information contained in input traces can be input source, type of action and associated data. Similarly, the traces collected and visualized in StoryPlay [44] are based on the theoretical framework of the NGLOB framework described earlier [20]. In addition to logging all user inputs, active variables, and the time taken for each scene, the system records updates to the internal state in all three adaptation dimensions: storytelling, gaming and learning. This consists of a history of visited scenes with their respective adaptation algorithm parameters based on associated and prerequisite skills, the narrative context as indicated by appropriateness values, player attributes describing the player model and the player's skill state. Generic game logs provide valuable information which can be used to assess learning games and identify strengths and weaknesses in their design. It also makes comparing different games possible. However, not all information is equally meaningful in all types of games. In addition, games can produce huge amounts of partially irrelevant data which must be filtered for analysis. For a detailed exploration and yet efficient analysis, it is thus recommendable to additionally tailor analytics to the specific game design features and evaluation requirements. Ideally, the game should be designed with analytics in mind. In other words, all major game mechanics in an "analytics-efficient" design are chosen in such a way as to directly reflect a learner's skill or behavior interesting in terms of evaluation [48] . An example of such a game is *Save Patch* presented in [23] where all player actions are tied to mathematical operations. The logging structure for this game was also designed to ensure no key information gets lost and no data significant to evaluation is overlooked. In [11], the authors suggest logging data at the "finest usable grain size", i.e. recording clearly defined, unambiguous events sufficient for understanding the context.

2.2 Capturing Data

To allow the integration of learning analytics, the game platforms should be able to record game traces and are usually also required to allow sending them to external servers for collection [44]. However, data useful for learning analytics is not limited to activity logs created by the game engine. Measuring engagement and learning can be done by combining data from different sources.

2.2.1 Multimodal Learning Analytics

Today more advanced technologies and sensors can capture data with different modalities. For example, measuring attention, effort and excitement within learning environments can benefit from biometric data like information about posture, facial expressions, eye tracking, pupil diameter, skin conductance, heart rate, respiration and EEG signals [30]. There are many challenges associated with this information-intensive approach. Not only can these types of data usually only be collected from a small group of people, but combining parallel streams of wireless data also produces complex and noisy results which are difficult to reduce and synchronize for analysis. On the other hand, this approach helps to identify significant events which might be overlooked using only extensive data. In addition, capturing rich modalities of communication using multimodal recordings (e.g. speech, digital pen, images and videos) can also be especially useful for evaluating collaborative learning settings [39]. In fact, traditional analytics based on clicks and keystrokes limit their integration into new technologies which no longer depend on mouse and keyboard for their input. An example of successfully combining multimodal data streams is described in detail in [8].

2.2.2 Mobile and Ubiquitous Learning Analytics

Smartphones present a promising platform for learning analytics because of their widespread availability and ease of use, flexibility, multimodality and personalization which makes gathering data much more natural and non-invasive than traditional platforms. As the terms Mobile and Ubiquitous Learning are becoming more and more popular, new terms like *Mobile and Ubiquitous Learning Analytics* are beginning to arise [6]. Mobile Learning Analytics is concerned with data of mobile learners resulting from their interactions with mobile devices, learning materials and other mobile learners while Ubiquitous Learning Analytics additionally consider contextual information about learners and their environment such as time, location, activity, noise, light and social environment. An example of an application which makes use of context information for learning is SCROLL (System for Capturing and Reminding of Ubiquitous Learning Log) [38]. Once the learner arrives at a place where s/he had a learning session before, s/he is reminded of the topic s/he learned at the same place. In addition, the learner can also select to view his/her own or other learners' learning log history of a selected time period or around a certain position. Another interesting question arises for learning systems which can be used on both PCs and handheld devices. The two versions of the software may not be identical, but rather complement each other, with one of them being recommended to the learner according to the current location or context [9].

2.3 Aggregating Data

After capturing extensive data from different users and different sources, datasets should be merged for statistical processing or data mining to be able to extract information from it. For intensive data, aggregation is also required to combine multiple streams of data captured by different devices about one and the same user. A key challenge for this process is the current lack of interoperability [12].

2.3.1 Aggregation across Users

Logs typically contain a large amount of data and thus usually undergo preprocessing before they are ready for analysis. Structuring, segmenting, filtering and normalizing raw data is done according to the application at hand. Using session identifiers, data from different users can then be joined into one central database. To enable this, the log files generated on all machines should be using the same data format.

There have been several attempts to standardize xml-based formats of log files for educational data mining applications. In [26], a data format for logging interactions of learners with tutoring systems is presented. Similarly, a format for encoding interactions within Computer Supported Collaborative Learning (CSCL) environments was introduced in [15]. An example of aggregating logs of multiple players in learning games was implemented for the tool StoryPlay described earlier where playtraces from individual sessions are combined into one comprehensive spreadsheet [42]. In [43], the use of *aggregation models* is proposed which use semantic rules to map game actions or states to meaningful expressions under which similar events are grouped.

2.3.2 Aggregation across Modalities

When gathering multimodal data to enrich the interpretation of log files, researchers are faced with many challenges during the aggregation phase [8, 15, 30]. Synchronizing data captured in parallel using different devices is necessary for observing behaviors at specific timestamps across data streams and for analyzing situations, confirming claims and drawing conclusions. Tools like *Replayer* are available which enable synchronized play of streams they captured and proved useful in such cases [36, 15]. In [8] the authors describe their time synchronization process for coordinating the encoding of several video streams on different machines, having their clocks synchronized using Network Time Protocol and communicating between processes using Smart Flow module [32]. Video and Audio files were then encoded into MPEG4 media streams. Digital ink files were hand synchronized using the *ChronoViz* multimodal analysis tool with their corresponding audio-visual files. An approach for synchronizing eye-tracking data and log events with EEG signals was presented in [30], where they were imported as hits at significant timestamps of the EEG traces to find correlations across channels .

2.4 Analyzing Data

After the aggregation stage, data can directly be used for reporting, i.e. statistics and abstracted overviews can be provided to the instructor or the learner whose task would be to extract useful patterns from the data. If the system is to analyze data automatically, as the case with adaptive educational games, then this stage is the most complicated, especially in games as real-time processing is required for personalization. Expressing it from the learning perspective, the gathered data should help get inferences about general traits and abilities of the learner, his general knowledge state, his situation-specific state, his learning behaviors and his learning outcomes [40]. From the gaming perspective, measures to be derived are general game performance, in-game learning and in-game strategies [11]. In the ECD approach described earlier, the Evidence Model describes the rules which govern the interpretation of in-game sources of evidence to infer competencies. Usually, algorithms are applied during learning sessions to update the competency model of the learner according to achievements and failures exhibited at runtime or more complex heuristics. Here, Bayesian networks can be used to update associated probability distributions of the different competencies [31]. In the 80Days project [24], the modeled knowledge structure is stored as a binary matrix, parsed at design time and then loaded during gameplay into the runtime component of the Skill Assessment Engine. According to the player's game interactions propagated by the Game Engine, the Skill Assessment Engine updates probabilities of corresponding skills whereas the Motivation Assessment Engine updates probabilities of aspects related to the learner's motivation like attention and confidence. In [23], Cluster Analysis was used to identify solution strategies and error patterns of players from learning logs. Error patterns were further classified into errors resulting from mathematical misconceptions and those related to game strategies. The author of [44] specified rules for interpreting semantic information from his gathered generic game traces described earlier. The idea is that by defining conditions on the variables like time spent on tasks or phases, values of in-game-variables or more complicated rules depending on the context, more insight into game experience and learning achievements can be gained. Similarly, it was possible, by focusing on certain intervals of biometric data streams where certain significant events were recorded in log files, to answer semantic questions [30]. Examples are finding out where the attention of the user was directed when a certain event occurred or if certain physiological responses are related to certain interactions. In another study a model based on Markov logic networks was proposed for recognizing player goals through their interaction in non-linear games [16]. Prediction is in this regard also a popular approach for analyzing logs. For example, real-time affect can be predicted in learning games using computational models as described in [29] or [22].

2.5 Deploying Results

Using inferences resulting from the interpretation stage can be done in two ways: Either this information is communicated to the instructor or the learner to empower him/her to make decisions on possible measures or interventions, or they are directly fed into adaptation mechanisms implemented in the game-based learning environment. The system can respond by choosing the appropriate next learning object or narrative event (macro-adaptivity) and/or adjusting aspects within a learning task like task difficulty or feedback type (micro-adaptivity) [24]. An example for making use of logs for enhancing learning experience in learning games through adaptation is Leo's pad, a smartphone application for children offering an early learning curriculum in an interactive playful environment [49]. Along with this application, Parent's Pad provides parents with useful insight into the learning activities and progress of their children. *Zoodles* [1] is another example of a parent dashboard for mobile educational games. Providing this kind of readable information to guide a learning experience is one of the main goals of LA. This is why a lot of studies were carried out to identify how to best visualize log data and learner models [13]. Hasse Diagrams are a popular way for graphically representing competency structures. In StoryPlay, visualization of logging information is realized using a replay component as well as different real-time visualizations of narrative structure, player model and skill tree, respectively. In [44] clicks on the screen were aggregated and visualized using heat maps to help identify which objects on the screen received more attention. The learning analytics toolbox eLAT [14] employs several visualization mechanisms which are not specifically targeting games but cover many aspects interesting for visualizing LA in Serious Games like real-time operation, extensibility and interoperability. Authors of [33] propose a technique for real-time learning analytics visualization for educational games applied on the example of an adventure game teaching computer networks. Two powerful and popular web analytics tools available for free use which can also be incorporated into learning apps and games are *Google Analytics* [2] and *Piwik* [3].

Virtual worlds like *Second Life* [4] and *OpenSimulator* [5] are increasingly being used for learning by creating immersive learning scenarios making use of the natural and rich environments and the multimodal and collaborative interactions as well as logging reports they offer [25]. An example for such a learning scenario is "Chatterdale Mystery", an English learning adventure game developed for OpenSim, is presented by the authors. Along with this game and as part of the Next-Tell project, a teacher control center software was implemented which offers easy-to-use tools for aggregating, analyzing and visualizing log files generated by OpenSim together with other sources within learning adventures allowing teachers to define and integrate their own evidence rules.

3. CONCLUSION

In this paper, we have described the state of the art in using learning analytics in the field of Serious Games. For modelling knowledge and skills within Serious Games, suitable approaches like Narrative Game-Based Learning Objects (NGLOB) and Evidence-Centered Design (ECD) have been investigated. Choosing which data is to be logged in Serious Games depends on learning goals, setting and tasks as well as game genre, mechanic and platform. Here we can differentiate between intensive and extensive data, single-player and multiplayer games and generic and game-specific traces. Ideally, games should be initially designed in a way where all game mechanics reflect learner states to make learning analytics more efficient. As games are played on different platforms and with different interaction mechanisms, relying solely on activity logs will not be suitable for all kinds of serious games. This is why terms like *Multimodal Learning Analytics* and *Mobile and Ubiquitous Learning Analytics* have arised which have also been presented in this paper as well as different tools useful for aggregating data across users and modalities. Deriving measures from gathered data can be done by defining conditions on generic or game-specific variables and events which reflect aspects like learning, strategies and motivation. In order to be used in games, this analysis is required to be carried out and its results deployed and/or visualized in real-time. Although there is an increasing amount of literature on this topic, there is a need for comprehensive guidelines, especially in the critical domains of interoperability, multimodality and mobility. Due to the complex nature of Serious Games, we argue that more focused efforts from researchers are needed for defining theoretical frameworks especially tailoring research on LA to this rich learning environment.

4. REFERENCES

[1] http://www.zoodles.com.

[2] http://www.google.com/analytics.

[3] http://piwik.org/.

[4] http://secondlife.com/.

[5] http://opensimulator.org/.

[6] N. R. Aljohani and H. C. Davis. Learning analytics in mobile and ubiquitous learning environments. In *11th World Conference on Mobile and Contextual Learning: mLearn 2012*, Helsinki, Finland, 2012.

[7] R. S. J. D. Baker and K. Yacef. The State of Educational Data Mining in 2009 : A Review and Future Visions. 1(1):3–16, 2009.

[8] P. Blikstein. Multimodal learning analytics. *Proceedings of the Third International Conference on Learning Analytics and Knowledge - LAK '13*, page 102, 2013.

[9] S. Bull, Y. C. Y. Cui, a.T. McEvoy, E. Reid, and W. Y. W. Yang. Roles for mobile learner models. *The 2nd IEEE International Workshop on Wireless and Mobile Technologies in Education, 2004. Proceedings.*, pages 124–128, 2004.

[10] S. Bull and J. Kay. Open learner models. In *Advances in Intelligent Tutoring Systems*, pages 301–322. Springer, 2010.

[11] G. K. Chung and D. S. Kerr. A Primer on Data Logging to Support Extraction of Meaningful Information from Educational Games: An Example from Save Patch. CRESST Report 814. *National Center for Research on Evaluation, Standards, and Student Testing (CRESST)*, page 27, 2012.

[12] A. Cooper. Learning Analytics Interoperability - The Big Picture In Brief. *Learning Analytics Community Exchange*, 2014.

[13] E. Duval. Attention Please!: Learning Analytics for Visualization and Recommendation. LAK '11, pages 9–17, New York, NY, USA, 2011. ACM.

[14] A. Dyckhoff and D. Zielke. Design and Implementation of a Learning Analytics Toolkit for Teachers. *Journal of ...*, 15:58–76, 2012.

[15] G. Dyke, K. Lund, and J.-J. Girardot. Tatiana: An Environment to Support the CSCL Analysis Process. In *Proceedings of the 9th International Conference on Computer Supported Collaborative Learning - Volume 1*, CSCL'09, pages 58–67. International Society of the Learning Sciences, 2009.

[16] B. M. Eun Young Ha Jonathan Rowe and J. Lester. Recognizing Player Goals in Open-Ended Digital Games with Markov Logic Networks. *Plan, Activity and Intent Recognition: Theory and Practice*, 2014.

[17] J.-C. Falmagne, D. Albert, C. Doble, D. Eppstein, and X. Hu. *Knowledge Spaces: Applications in Education.* Springer Science & Business, 2013.

[18] I. Garcia, A. Duran, and M. Castro. Comparing the effectiveness of evaluating practical capabilities through hands-on on-line exercises versus conventional methods. In *Frontiers in Education Conference, 2008. FIE 2008. 38th Annual*, pages F4H–18–F4H–22, Oct 2008.

[19] S. Göbel, M. Gutjahr, and S. Hardy. Evaluation of Serious Games. *Serious Games and Virtual Worlds in Education, Professional Development, and Healthcare*, page 105, 2013.

[20] S. Göbel, V. Wendel, C. Ritter, and R. Steinmetz. Personalized, adaptive digital educational games using narrative game-based learning objects. pages 438–445. Springer, 2010.

[21] S. L. . B. H. Jan Plass. Assessment mechanics: design

of learning activities that produce meaningful data. New York University, CREATE Lab, Apr. 2013.

[22] K. E. B. E. W. Joseph Grafsgaard Joseph Wiggins and J. Lester. Predicting Learning and Affect from Multimodal Data Streams in Task-Oriented Tutorial Dialogue. In *Seventh International Conference on Educational Data Mining*, 2014.

[23] D. S. Kerr and G. K. W. K. Chung. *Using Cluster Analysis to Extend Usability Testing to Instructional Content. CRESST Report 816*. National Center for Research on Evaluation, Standards, and Student Testing (CRESST), May 2012.

[24] M. D. Kickmeier-Rust and D. Albert. *An Alien's Guide to Multi-Adaptive Educational Computer Games*. Informing Science, 2012.

[25] M. D. Kickmeier-Rust and D. Albert. Learning analytics to support the use of virtual worlds in the classroom. In *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data*, pages 358–365. Springer, 2013.

[26] K. R. Koedinger, R. Baker, K. Cunningham, A. Skogsholm, B. Leber, and J. Stamper. A data repository for the EDM community: The PSLC DataShop. *Handbook of educational data mining*, pages 43–55, 2010.

[27] J. Konert, K. Richter, F. Mehm, S. Göbel, R. Bruder, and R. Steinmetz. Pedale - a peer education diagnostic and learning environment. *Journal of Educational Technology & Society*, 2012.

[28] K. Korossy. Modeling knowledge as competence and performance. *Knowledge spaces: Theories, empirical research, and applications*, pages 103–132, 1999.

[29] J. Lester, B. Mott, J. Rowe, and J. Sabourin. –learner modeling to predict real-time affect in serious games. *Design Recommendations for Intelligent Tutoring Systems*, page 201, 2013.

[30] S. M. Letourneau. Intensive data at CREATE - Research approaches & future directions. In *Simulations and Games Learning Analytics and Data Mining Workshop*, 2013.

[31] R. Levy. *Dynamic Bayesian Network Modeling of Game Based Diagnostic Assessments*. CRESST Report, 2014.

[32] C. Martin, O. Galibert, M. Michel, F. Mougin, and V. Stanford. NIST Smart Flow System User's guide.

[33] M. Minović and M. Milovanović. Real-time learning analytics in educational games. pages 245–251. ACM, 2013.

[34] R. J. Mislevy, R. G. Almond, and J. F. Lukas. A brief introduction to evidence-centered design. cse report 632. *US Department of Education*, 2004.

[35] A. Mitrovic and B. Martin. Evaluating the effect of open student models on self-assessment. *International Journal of Artificial Intelligence in Education*, 17(2):121–144, 2007.

[36] A. Morrison, P. Tennent, and M. Chalmers. Coordinated visualisation of video and system log data. In *Coordinated and Multiple Views in Exploratory Visualization, 2006. Proceedings. International Conference on*, pages 91–102. IEEE, 2006.

[37] K. Nurmela, E. Lehtinen, and T. Palonen. Evaluating CSCL log files by social network analysis. In *Proceedings of the 1999 conference on Computer support for collaborative learning*, page 54. International Society of the Learning Sciences, 1999.

[38] H. Ogata, M. Li, B. Hou, N. Uosaki, M. M. El-Bishouty, and Y. Yano. SCROLL: Supporting to share and reuse ubiquitous learning log in the context of language learning. *Research & Practice in Technology Enhanced Learning*, 6(2), 2011.

[39] S. Oviatt, A. Cohen, and N. Weibel. Multimodal learning analytics: Description of math data corpus for icmi grand challenge workshop. In *Proceedings of the 15th ACM on International conference on multimodal interaction*, pages 563–568. ACM, 2013.

[40] J. L. Plass, B. D. Homer, C. K. Kinzer, Y. K. Chang, J. Frye, W. Kaczetow, K. Isbister, and K. Perlin. Metrics in Simulations and Games for Learning. In *Game Analytics*, pages 697–729. Springer, 2013.

[41] M. Prensky. Computer games and learning: Digital game-based learning. *Handbook of computer game studies*, 18:97–122, 2005.

[42] C. Reuter, F. Mehm, S. Göbel, and R. Steinmetz. Evaluation of Adaptive Serious Games using Playtraces and Aggregated Play Data. *Proceedings of the 7th European Conference on Game Based Learning (ECGBL) 2013*, (October):504–511, 2013.

[43] A. Serrano, E. J. Marchiori, A. del Blanco, J. Torrente, and B. Fernández-Manjón. A framework to improve evaluation in educational games. In *Global Engineering Education Conference (EDUCON), 2012 IEEE*, pages 1–8. IEEE, 2012.

[44] A. Serrano-Laguna, J. Torrente, P. Moreno-Ger, and B. Fernández-Manjón. Application of learning analytics in educational videogames. *Entertainment Computing*, 2014.

[45] V. J. Shute, M. Ventura, M. Bauer, and D. Zapata-Rivera. Melding the power of serious games and embedded assessment to monitor and foster learning. *Serious games: Mechanisms and effects*, pages 295–321, 2009.

[46] G. Siemens and R. S. J. Baker. Learning Analytics and Educational Data Mining : Towards Communication and Collaboration. 2010.

[47] K. K. Tatsuoka. Architecture of knowledge structures and cognitive diagnosis: A statistical pattern recognition and classification approach. *Cognitively diagnostic assessment*, pages 327–359, 1995.

[48] T. P. Vendlinski, G. C. Delacruz, R. E. Buschang, G. Chung, and E. L. Baker. Developing high-quality assessments that align with instructional video games (CRESST Report 774). . *National Center for Research on Evaluation, Standards, and Student Testing*, 2010.

[49] A. V. Wallop. Althea Vail Wallop CS 229 Final Project Report Learning to Predict Disengagement in Educational iPad Application. pages 1–5, 2010.

[50] J.-D. Zapata-Rivera and J. E. Greer. Interacting with inspectable bayesian student models. *International Journal of Artificial Intelligence in Education*, 14(2):127–163, 2004.