Analyzing Player Behavior in Digital Game-Based Learning: Advantages and Challenges

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Abstract: In our article, we argue for enhanced consideration of player behavior as a third variable in research concerning game-based learning. Due to the fact that games are interactive non-linear learning environments, there are different ways to play. This way it is possible that users do not interact with the educational game, features of the game or the treatment as intended, or that they interact differently according to their different player behavior. If not considered, this is a thread for intervention integrity in studies on game-based learning. With examples from current research we underline this statement. In addition to the main research questions of each study, we consider examination of the following questions as highly relevant: 1. Are there subgroups of players regarding player behavior? 2. Do all these subgroups interact with the educational game/the treatment as intended? 3. Are there different effects of the game/the treatment depending on player behavior? Describing the advantages and drawbacks of methods for monitoring and analyzing player behavior, we suggest log files and data mining methods as appropriate tools for the examination of player behavior. In a study on an educational adventure game, we examine the method and the benefits in more detail. In our study the cluster analysis of the log files indicates that it is suitable to distinguish between two different subgroups of players who show two patterns of player behavior – intensive object exploration in Cluster 1 and intensive interaction with non-player characters (NPCs) in Cluster 2. We consider that taking player behavior into account enables the researcher to get an insight into underlying mechanisms which might result, for example, in different learning outcomes. Furthermore, the inclusion of player behavior into analysis is a precondition for tailored instruction.

Keywords: interactive learning environments, game-based learning, log files, player behavior

1. Introduction

In the research area of game-based learning, researchers frequently state the need for empirical studies which close the gap between the increasing amount of educational games and the poor knowledge concerning effective instructional design of these learning environments (e.g., Ke 2009; Mayer 2011). In this paper, we highlight a challenge which goes hand in hand with this type of research. Educational games are interactive and mostly non-linear. It is a main characteristic of digital games that a user is in control of the storyline or outcome. The course of a game and player experiences depend on the players' actions within the game.

There exists a theoretical approach which deals with different player behavior in games – Bartle's model on player types (Bartle 1996, 2014). In his study on Multi-User Dungeon games, he differentiates between four types of players. He locates them along two continuous dimensions – whether players like to interact with or to act on things and whether they are more interested in other players or the game world. The player types are not elusive, a mixture is also possible. These player types are:

- Socializers, who are mainly interested in social interaction in the game,
- Explorers, who like to explore the game, solving all the puzzles and interact with the objects in the game,
- Achievers, who are mainly interested in reaching the goals of the game and therefore collecting character points, money or objects.
- Killers, who want to act on other players and are interested in all kinds of tournament,

Over the last years, research on player types and player behavior became more and more relevant, especially for commercial game development. Working initially with surveys, researchers nowadays also focus on in-game data for analyzing user-game interaction (Drachen, A, Sifa, R, Bauckhage, C & Thurau, C 2012; Seif El-Nasr, M., Drachen, A. & Canossa, A. 2013). Regardless, there are not many approaches to consider player types in studies on game-based learning (Xu, Poole, Miller, Eiriksdottir, Kestranek, Catrambone, & Mynatt 2012). However, it might be worth to ask research questions like: Can we distinguish between different player types

in educational games? If so, is there any effect of player type on motivational or cognitive variables? A majority of studies concerning game-based learning does not take the possibility of different player behavior into account. In these studies the game is treated as a "black box" (e.g., Adams, Mayer, MacNamara, Koenig, & Wainess 2012; Barlett, Harris, & Baldassaro 2007; Ke & Grabowski 2007). This is a threat to intervention integrity and thus, to the validity of results (Ennemoser 2009). The intervention integrity depends on a successful implementation of an independent variable. Moreover, in studies on game-based learning, intervention integrity requires an adequate use of the game as a learning environment. This does not only apply to studies analyzing the effects of educational games in comparison to a non-game control group, but also for studies comparing different instructional principles for game design. For example, in a recent study, Adams et al. (2012) examined the effects of narration on game-based learning. They compared the learning outcomes of three groups of students. Two groups played a narrative or a non-narrative version of an educational adventure game. The third group was in a non-game condition; they learned the same content with a slide-show. Somewhat contrary to expectations, the narrative group was not superior to the non-narrative group in the learning tests, however, the non-gaming group outperformed both. As one possible explanation for their results, the authors noted that "the game may have been somewhat tedious, in that the players had to expend much effort in trivial tasks such as walking from place to place, picking up and carrying objects, and navigating" (Adams et al. 2012, p. 247). This statement illustrates the problems which arise from not analyzing player behavior. The researchers can only guess how their participants interacted with the game. There could, for example, be a group of players that liked to explore the game world. There could be another group of players that had difficulties playing the game (e.g., because they did not know what to do next). Therefore, such a group of players might not have adequately interacted with the learning content, but only walked from scene to scene or carried objects without using them properly. A similar phenomenon is known from research on E-Learning environments as "lost in hyperspace". When a learner is "lost", a structural disorientation is often accompanied by a conceptual disorientation, resulting in problems to build coherent mental representations of learning content (e.g., Otter & Johnson 2000). Therefore, the first challenge for the validity of results might arise from non-adequate use of educational games as learning environments. We highlight this problem with results of another empirical study on game-based learning where the player behavior was measured. The object of the analysis in this study was an educational adventure game with learning content which was not integrated in gameplay, but opened at different points in the scenario (Kerres & Bormann 2009). Results indicate that there were two different patterns of player behavior. Whereas one group of players interacted with the learning content as intended, a majority of players simply skipped this content. Of course, only students who processed the learning content could actually learn. Without taking the usage of learning content into account, the conclusions from the study would have led in the wrong direction, namely that (for whatever reason) it is not possible to learn from such a game. Because the authors analyzed the player behavior, they came to the conclusion that a better integration of the learning content in the game might be crucial. Another challenge for validity arises when the treatment, i.e. a specific instructional feature, is not used as intended. The study from Nelson (2007) provides a good example: He analyzed the effects of a guidance system in an educational game on learning outcome. He could not identify differences between the group with guidance and the group without guidance. He discovered through an assessment of the users' handling of the guidance system that a majority of participants in the guided group did not use the system at all. The intervention was not implemented as intended. Without analyzing player behavior, Nelson might have concluded that guidance as an instructional feature in game-based learning does not work at all.

The analysis of player behavior in educational games where the learning content is fully integrated in the game is likewise important. If the learning content is integrated in dialogs, for example, players who are more engaged in fighting enemies might not actually find this content. In this example, an instructional feature which works perfectly well for one player group might not be effective for another. The aforementioned user who does not get in contact with the relevant learning content might benefit from a guidance system, whereas the same guidance is irrelevant or even redundant for users whose behavior is characterized through an emphasis on dialogs and, therefore, a huge amount of interaction with learning content. Thus, the third challenge for validity in studies on game-based learning is the possibility of different treatment effects depending on player behavior.

To sum up, it is possible that users do not interact with the educational game, features of the game, or the treatment as intended, or that they interact differently according to their different player behavior. Hence, we consider measurement of player behavior as crucial for valid statistical research concerning game-based

learning. In addition to the main research questions of each study, we consider examination of the following questions as highly relevant:

- Are there subgroups of players regarding player behavior?
- Do all these subgroups interact with the educational game/the treatment as intended?
- Are there different effects of the game/the treatment depending on player behavior?

By taking the player behavior into account, it is possible to ensure intervention integrity and to answer the validation question whether the results for the whole group of players also hold for subgroups of players. Furthermore, analyzing player behavior is a precondition for tailored instructions.

2. Recording and analyzing player behavior in educational games

Monitoring player behavior can be carried out in different ways, for example, observations via camera or human observers. However, computer-based assessments bear advantages for analysis because these methods are non-intrusive and do not influence players' behavior or gameplay experience because they usually are not aware of the recording (Linek, Marte, & Albert 2008). From an ethical point of view, it is not only necessary to inform participants about the assessment afterwards, but also to collect the information without a link to the real user names (e.g., through encoding).

Methods like computer-based videotaping provide researchers with an all-embracing record of user-system interactions, which has to be hand-coded before analysis. This method is extremely time-consuming and prone to measurement or coding errors. A more suitable method is the recording of actions in log files, which are automatically written in the background. Log files are protocols of the user-system interactions. Every user interaction has to be recognized and stored. The fine-grain level of interaction information, for example, at time point 1:02:15 mouse click at position (564,345), has to be preprocessed and interpreted. It is necessary for analysis that each log file is assigned to a specific user code. The use of log file recording to monitor player behavior has two main benefits compared to other computer-based observation methods:

- Researchers determine relevant events in preparation of the logging. This is a filtering of the complete information space. Therefore, it is possible to collect only click or error rates, but also to log, in fact, every interaction. This pre-selection of data to be stored decreases the complexity of data processing.
- Log files can be stored as machine-readable data. Hand-coding is not necessary. In this way, researchers can reduce time and effort as well as coding errors.

Requirements for using log files are access to source code or other technical properties of the learning system. This includes capabilities of IT system development or the use of specialized analysis tools for logging mouse or keyboard interactions.

As a result of log file assessment, player behavior is represented by a dataset. Depending on the game, context, user, and experimental design, a dataset contains a lot of information. Involved variables create a multi-dimensional dataset which can be used as a basis for further analyses, such as statistics, pattern identification, or reduction and aggregation. This sometimes overwhelming amount of data is a drawback of using log files. However, there are methods which provide a possibility to manage the flood of information from these observations. Data mining methods enable the detection of patterns in multi-dimensional data spaces. It is a collection of different methods, as well as algorithms within these methods. A choice of method and algorithm has to be made depending on targets, data, and restrictions. Different data mining procedures exist that are useful for studies concerning game-based learning (see for commercial games also Drachen et al. 2012 or Seif El-Nasr et al. 2013).

Classification of objects into abstract classes is a method that supports systematization (Kohavi & Quinlan 2002). A classical tool in this domain is the decision tree, which enables decision support in a tree-based model. A membership of an object to a subset or group can be determined with a decision tree. The learning outcome for game-based learning might be the classification of interest. This can be carried out with properties of player behavior, such as reading texts, viewing pictures, or click rates in the game. A decision tree uses these variables to determine which player behavior corresponds to which class of learning outcome.

Decision trees make it possible to include typical group identification questions and, in this way, to make game-based learning more adaptive.

Association rule learning is a data mining technique to identify strong rules or relations between objects (see, for instance Buneman, Jajodia, Agrawal, Imieliński, & Swami 1993). Association rules are used in practice, for example, to analyze customers' supermarket baskets, and thus, to improve store layout or to prepare merchandizing campaigns. Relationships are discovered that co-occur as activities of users or groups in the data. In an educational game, these rules enable the identification of different paths through the game, and thus, to improve the game's usability by providing recommendations.

Clustering methods are used to group similar objects that are described by their properties (for details see, for example, Kaufman & Rousseeuw 2005). This is often a multivariate analysis technique to assign objects to a group and, therefore, to reduce dimensionality. However, an interpretation of a cluster is necessary to identify similarities of elements. With clustering methods, we can identify different groups of players on the basis of their behavior. Therefore, clustering is the method of choice regarding the question of intervention integrity and generalizability of results concerning different player behavior.

In a study on an educational adventure game, we examined this approach. In the following, we present some details.

3. Material and methods

3.1 Participants, design, and procedure

The participants of our study were 64 (male: 29; female: 35) 14- to 16-year-old students (µ: 15.03; SD: 0.69) from German secondary schools. The game was played in the computer labs of the schools. Each student was sitting in front of a computer and played the game on her own. The playing time was 68 minutes on average (SD: 9,1). Immediately after the end of the game, the students filled out a demographic survey and two questionnaires – one for measuring intrinsic motivation and one for measuring learning performance. There was no time restriction for playing and filling out the questionnaires. There was a de-briefing session after the end of the study where the goal and structure of the study were explained.

3.2 Material

The learning environment is the digital educational game "1961" for history lessons (Hawlitschek 2013). The game deals with an important event of modern German history – the building of the Berlin Wall in 1961. The content of this adventure game is based on the curriculum of 10th grade in secondary schools in Germany. The player's avatar travels back in time to the year 1961 by mistake. He has to return to his time as soon as possible, but the time machine needs a new battery. The player has to explore the virtual historical situation to play the game successfully (see Figure 1).

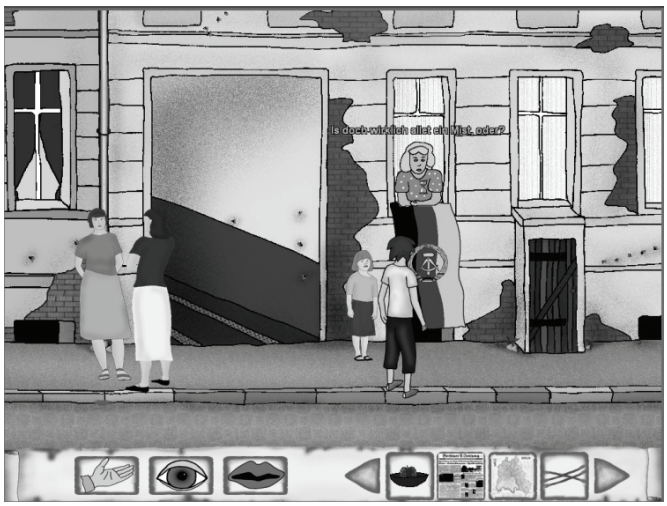

Figure 1: Screenshot "1961"

As in many educational games, the learning content is integrated into the game world and activities that are irrelevant for learning are possible. Learning content is mainly mediated through the communication with non-player characters and, to a lesser extent, through the exploration of different objects.

We used a slightly modified questionnaire from Isen & Reeve (2005) to measure intrinsic motivation. This questionnaire (Cronbach's α = .90) contains six items that measure situational interest, curiosity, and fun on a 7-point Likert scale ranging from "strongly agree" (= 1) to "strongly disagree" (= 7).

Previous knowledge was tested two weeks before with a pre-test, which consisted of four open questions concerning the historical situation. The students' learning performance was measured with open questions directly after playing the game. The test was divided into two parts: We used five questions for a recall test. These questions remained in the context of the game. The participants had to remember facts with which they were confronted during the game. The four questions concerning transfer were the same as in the pre-test. To answer them after playing, the participants had to interpret facts they remembered from the gameplay with reference to the historical situation. For this purpose, participants had to transfer knowledge from the game world into the real world context. One question, for example, asked for arguments a representative of the East German government would use to explain the necessity of building the Wall. This is not explicitly mentioned in the game, but could be extracted from comments of non–player characters (NPC) or from texts in objects such as a virtual newspaper. Two researchers rated the learning test on the basis of a solution model. We achieved satisfying inter-coder reliability (Cohen's kappa of 0.8 for both measures).

3.3 Measurement of player behavior

We specified two main classes for the log file assessment: touch, view, and talk, (as actions) and NPC, scene objects and inventory objects (as objects), see Figure 2.

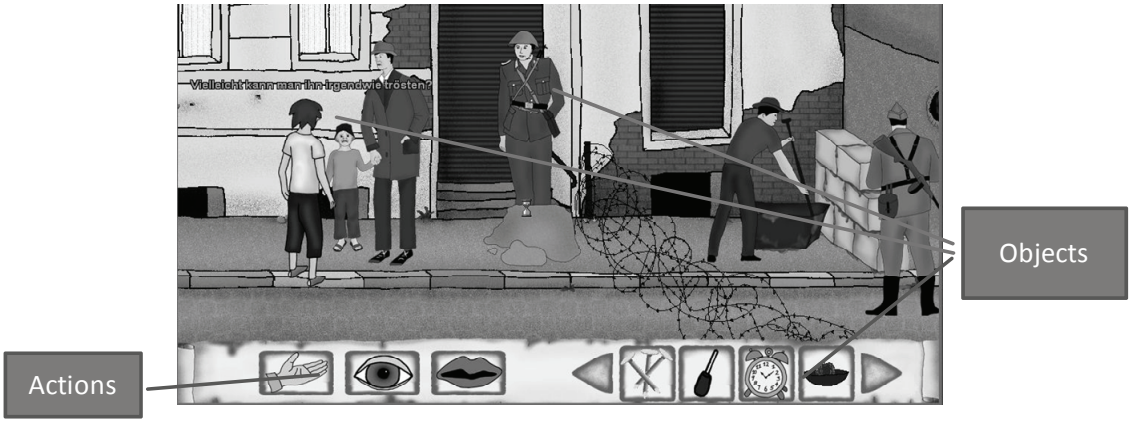

Figure 2: Scene from "1961" with actions and objects

Actions are specified in more detail in combination with objects. As an example, when the user touches an object from the inventory and uses it with another object, the action is stored as "combine." In addition to these actions (type and detailed information), we also logged time (machine time). This enabled us to interpret the data in a sequential way. We stored our system information in a log file with the requirement that it is readable for both, researcher and machine. Therefore, we used HTML; a short excerpt is given in Figure 3. On the left is time information, the middle part represents the action types, and the right part has detailed information on the objects involved, scene changes, or dialogs. Furthermore, we used colors to differentiate easily between different types of action. A computer program counted the number of different action types (see **Error! Reference source not found.**) and the time in dialogs in a data preprocessing.

Table 1: Overview of variables concerning the action types

Action type:	Touch	View	Talk
Variable:	- "take/press/open" - "combine"	- "view"	"dialog" "time in dialogs"

11:22:47	Combine	Wire with Rope
11:23:15	Take/Press/Open	Suitcase
11:23:40	Take/Press/Open	Purple Blanket
11:23:46	Take/Press/Open	Blanket
11:23:55	Game	Loading Scene 4b
11:24:01	Game	Loading Scene 4a
11:24:10	Game	Loading Scene 3
11:24:25	Take/Press/Open	Soldier 1
11:24:51	Take/Press/Open	Barbwire
11:24:57	Dialog:	Soldier
11:25:09	Kasi:	Why does barbed wire lie in the middle of the street here?
11:25:34	Border Guard:	This is now all a border area. The people over there are our enemies. They are all taking our money and everything else. Everyone who wants to go there is our enemy, too! What do you want to do?

Figure 3: Excerpt of a log file from "1961"

Additionally, we computed the time a subject spent in the game ("time in game") and the number of scene changes ("scene changes"). With these measures, we came up with seven variables for player behavior in our experiment. In the next step, the identification of subgroups of users according to player behavior was possible with cluster analysis. Player behavior was thus operationalized through cluster assignment.

The first step of cluster analysis is to select an appropriate algorithm. We used "partitioning around medoids" (Kaufmann & Rousseeuw 2005), also called k-medoids, due to the fact, on the one hand, that it is quite easy to use, and, on the other hand, can handle outliers that are included in our data. With the k-medoids algorithm, a center of a group (cluster) is represented by an existing data point and outliers have less influence compared to mean value-based algorithms, such as k-means (Lloyd 1982). One challenge of clustering algorithms is that the number of clusters has to be determined as an input parameter. We applied Bayesian Information Criteria (BIC) and the Elbow method to select the cluster parameter (Schwarz 1978). As a result of both methods, we obtained two as the cluster parameter for the k-medoids algorithm.

4. Results

We examined our data in three steps in an exploratory analysis. We applied the k-medoids algorithm as a first step to examine whether there were subgroups of players regarding player behavior. As a result of this cluster analysis, we obtained an assignment into one of two clusters for each subject. Cluster 1 contains 40 students (male: 20; female: 20). Cluster 2 contains 24 students (male: 9; female 15). We analyzed with ANOVAs whether the clusters actually represent different groups according to player behavior. The seven variables that are included in the data mining algorithm are used as dependent variables. The results of the ANOVAs (Table 2) yielded no significant differences concerning the variables "scene change" and "take/press/open." However, the students in Cluster 1 had significantly higher values in "view" and "combine" than the students in Cluster 2. These, in turn, had significantly higher values in "dialogs" and spent significantly more "time in dialogs" and "time in the game". The difference between both clusters can be described in terms of intensity of interaction with NPCs or objects. While the students in Cluster 1 are more interested in object exploration, the students in Cluster 2 are more engaged in communication with NPCs.

Table 2: Results of the ANOVAs for both cluster groups

Variable	Result of ANOVA
"view"	$F(1,63) = 4.53,\ p < .05,\ \eta^2 = .07$
"take/press/open"	$F(1,63) = 0.00,\ p = 1.0\ \ \eta^2 = .00$
"combine"	$F(1,63) = 5.05,\ p < .05,\ \eta^2 = .08$
"dialogs"	$F(1, 63) = 22.60,\ p < .001,\ \eta^2 = .27$
"time in dialogs"	$F(1, 63) = 52.32,\ p < .001,\ \eta^2 = .46$
"time in game"	$F(1, 63) = 62.49,\ p < .001,\ \eta^2 = .32$
"scene changes"	$F(1, 63) = 1.18,\ p = .28,\ \eta^2 = .02$

In the second step, we searched exploratory for differences concerning motivation and learning which arise from different player behavior. In this way, we examined whether both subgroups interacted with the game as intended.

Our analysis confirmed that there was no significant difference between the two clusters concerning their intrinsic motivation ($F(1, 63) = 0.38$, $p = .54$, $\eta^2 = .01$). Furthermore, there was no difference in factual recall ($F(1, 63) = 0.55$, $p = .46$, $\eta^2 = .01$) and transfer ($F(1, 63) = 0.14$, $p = .70$, $\eta^2 = .00$).

Table 3: Mean scores and standard deviations for both clusters on three measures

	Group					
	Cluster 1		Cluster 2			
Measure	μ	SD	μ	SD		95%CI
Recall	6.9	2.19	7.33	2.39		[6.50; 7.63]
Transfer	4.23	2.11	4.42	1.64		[3.81; 4.78]
Intrinsic Motivation	.03	1.09	-0.13	0.82		[-.28; .22]

Players in Cluster 1 ($t(30) = 2.93$, $p = .001$, $d = 0.56$) and in Cluster 2 ($t(19) = 2.21$, $p = .03$, $d = 0.69$) had a significant knowledge gain from pretest to post-test.

5. Discussion

In this paper, we argue for consideration of player behavior in analysis of game-based learning. The cluster analysis of the log files indicates that it is suitable in our study to distinguish between two different subgroups of players who show two patterns of player behavior – intensive object exploration in Cluster 1 and intensive interaction with non-player characters in Cluster 2. We show that Bartle's player types could be found in an educational adventure game. However, we only found two of four player types. The players in Cluster 2 are Socializers according to Bartle's definition and the player in Cluster 1 are Explorers. This result can be explained due to the genre of the game. An adventure game is most suitable for exploration of the game world as well as communication with NPCs. On the other hand, there is no real opportunity to fight with opponents and possibilities for achievements are rare.

We do not identify that different player behavior results in different motivation and learning outcome. This result is a bit surprising. In the game, learning content predominantly is mediated through the communication with non-player characters. Whereas almost all dialogs in the game contain learning content, this is not the same for the objects. In the game "1961", there are objects which are relevant for learning as well as objects which are relevant only for player's enjoyment. Since the player behavior of the Socializers is characterized through a high amount of communication with NPCs, they get in contact with a large part of the learning content. It could have been that this would also influence the learning outcome. Nevertheless, the game works well for both types of players with respect to learning outcome and motivation.

We see a rich area for future research in combining fine-grained analysis of player behavior with data on motivational and cognitive variables. In our study, we examined motivation and learning outcome but there are more relevant variables, which are likely associated with behavior in the game, e.g., self-regulation, attitudes towards the game and the learning content, or flow experience. In the future, it might be standard that the design of educational games and the design of interventions can be adapted to the needs of particular types of players or learners.

We consider that taking player behavior into account in research on game-based learning enables the researcher to get an insight into underlying mechanisms which might result, for example, in different learning outcomes. Computer-based methods provide the possibility to assess the behavior of the players without their awareness, and thus, without measurement effects. However, it is necessary to think about ethical problems, which might arise from this kind of measurement. Therefore, we collected the data encoded in such a way that there was no link between data and personal information of players. Furthermore, we did a de-briefing session after the study. There we explained our research goals and methods. At this point, it was possible for players to intervene if they did not want their data to be included in our analysis. However, nobody intervened.

As result from our study, we conclude that monitoring and analyzing player behavior via log file and clustering methods is a useful and easily applicable approach for controlling intervention integrity. The precondition for considering player behavior as a variable is the recording of the gameplay. Knowledge of appropriate IT programs or cooperation with game developers is necessary to collect these log files. This might be daunting at first glance. However, the inclusion of player behavior into analysis (e.g., as a moderator variable) is suitable for improving the validity of experiments in game-based learning and a precondition for tailored instructions.

References

Adams, D. M., Mayer, R. E., MacNamara, A., Koenig, A. and Wainess, R. (2012) "Narrative games for learning: Testing the discovery and narrative hypotheses", *Journal of Educational Psychology*, *104*, pp 235–249.

Barlett, C. P., Harris, R. J., and Baldassaro, R. (2007) "Longer you play, the more hostile you feel: Examination of first person shooter video games and aggression during video game play", *Aggressive Behavior*, *33*, pp 486–497.

Bartle, R. A. (1996) "Hearts, clubs, diamonds, spades: Players who suit MUDs", *Journal of Virtual Environments 1*, [online], http://www.mud.co.uk/richard/hcds.htm.

Bartle, R. A. (2014) Design principles: Use and Misuse. In: T. Quandt and S. Kröger (Eds.), *Multiplayer. The social aspects of digital gaming*, Routledge, New York, pp. 10-22.

Buneman, P., Jajodia, S., Agrawal, R., Imieliński, T. and Swami, A. (1993) "Mining association rules between sets of items in large databases", *Proceedings of the 1993 ACM SIGMOD international conference on Management of data – SIGMOD '93*: ACM Press, pp 207–216.

Drachen, A, Sifa, R, Bauckhage, C and Thurau, C (2012) 'Guns, Swords and Data: Clustering of Player Behavior in Computer Games in the Wild', *Proceedings of CIG 2012. IEEE*, pp 163-170.

Ennemoser, M. (2009) Evaluating the potential of serious games. What can we learn from previous research on media effects and educational intervention? In: U. Ritterfeld, M. Cody and P. Vorderer (Eds.), *Serious games. Mechanisms and effects*, Routledge, New York, pp 344–373.

Hawlitschek, A. (2013) *Spielend lernen. Didaktisches Design digitaler Lernspiele zwischen Spielmotivation und Cognitive Load*, Logos, Berlin.

Isen, A. M. and Reeve, J. (2005) "The influence of positive affect on intrinsic and extrinsic motivation: Facilitating enjoyment of play, responsible work behavior, and self-control", *Motivation and Emotion*, 29, pp 295-323.

Kaufman, L. and Rousseeuw, P. J. (2005) *Finding groups in data. An introduction to cluster analysis*, Wiley, Hoboken, NJ.

Ke, F. (2009) A qualitative meta-analysis of computer games as learning tools, In: R. E. Ferdig (Ed.), *Handbook of research on effective electronic gaming in education*, IGI Global, New York, (pp. 1–32).

Ke, F. and Grabowski, B. (2007) "Gameplaying for maths learning: Cooperative or not?", *British Journal of Educational Technology*, *38*, pp 249–259.

Kerres, M. and Bormann, M. (2009) "Explizites Lernen in Serious Games: Zur Einbettung von Lernaufgaben in digitalen Spielwelten", *Zeitschrift für E-Learning, Lernkultur und Bildungstechnologie*. Themenheft: Serious Games, *4*, pp 23–34.

Kohavi, R. and Quinlan, R. J. (2002) Data mining tasks and methods: Classification: decision-tree discovery, In: W. Klösgen and J.M. Zytkow (Eds.), *Handbook of data mining and knowledge discovery,* Oxford University Press, Oxford, Berlin, pp. 1–32.

Linek, S. B., Marte, B. and Albert, D. (2008) "The differential use and effective combination of questionnaires and logfiles", *Proceedings of the International Conference on Interactive Computer Aided Learning (ICL)*. Special Track "Computer-based Knowledge & Skill Assessment and Feedback in Learning settings", pp 1–8.

Lloyd, S. (1982) "Least squares quantization in PCM", *IEEE Transactions on Information Theory*, *28*, pp 129–137.

Mayer, R. E. (2011) Multimedia learning and games, In: S. Tobias and J. D. Fletcher (Eds.) *Computer games and instruction*, State University of New York, Albany, pp 1–32.

Nelson, B. C. (2007) "Exploring the use of individualized, reflective guidance in an educational multi-user virtual environment", *Journal of Science Education and Technology*, *16*, pp 83–97.

Otter, M. and Johnson, H. (2000) "Lost in hyperspace: metrics and mental models", *Interacting with Computers*, *13*, pp 1-40.

Schwarz, G. (1978) "Estimating the dimension of a model", *The Annals of Statistics*, *6*, pp 461–464.

Seif El-Nasr, M., Drachen, A. and Canossa, A. (2013) *Game Analytics, Maximizing the Value of Player Data*, Springer, London, Heidelberg, New York.

Xu, Y., Poole, E. S., Miller, A. D., Eiriksdottir, E., Kestranek, D., Catrambone, R. and Mynatt, E. D. (2012) "This is not a one-horse race: understanding player types in multiplayer pervasive health games for youth", *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, pp 843-852.