Individualization in Serious Games: A Systematic Review of the Literature on the Aspects of the Players to Adapt To

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Abstract

It has been extensively argued that individualizing a serious game to the characteristics of its players is a major contributing factor to its effectiveness. To realize this individualization, the identification of player aspects that can be used as input is essential. Despite its importance, research works that review and highlight the most widely used player aspects for the individualization of serious games are lacking. This article presents a systematic literature review (SLR) on this topic and provides an overview of the empirical evidence from the literature on the effect of individualization on players' experiences, learning, or other outcomes. The results of this SLR show that aspects of players related to performance (e.g., in-game and task skill measures) are among the most frequently researched ones for individualization, while aspects pertaining to physiological states (e.g., attention, stress) or personal traits (e.g., learning style, intelligence) are less studied. This SLR will help researchers and practitioners in making informed decisions regarding what aspects of players have yielded successful individualization in a serious game. The paper also points to aspects and subjects on which research is lacking such as user data from extended reality headsets, Geo-location data, and data fusion.

Keywords: Individualization, Adaptation, Personalization, Customization, Serious Games, Systematic Literature Review, Empirical Evidence, Learning Effectiveness, Game Experience
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1. Introduction

Serious games are defined by Ritterfeld et al. as *"any form of interactive computer-based game software for one or multiple players to be used on any platform and that has been developed with*

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the intention to be more than entertainment" ([1], Page 6). On similar grounds, Dörner, Göbel, & Effelsberg define a serious game as *"a digital game created with the intention to entertain and to achieve at least one additional goal (e.g., learning or health). These additional goals are named characterizing goals"* [2], and refer to user and not to company goals (such as making money). Examples of additional primary purposes are training, education, rehabilitation, attitude and behaviour change, and much more. In this sense, learning games or educational games also belong to the group of serious games.

The importance of considering individual differences among players when designing and effectuating a serious game has been raised by many researchers and in different contexts (e.g., [3, 4, 5, 6, 7, 8]). For instance, Charles et al. [3] have stated that people learn in different ways, at different paces, and based on different learning styles. Additionally, people employ different playing strategies and styles during gameplay (e.g., [9, 10, 11]). Moreover, the range of skills and capabilities among the players may vary (e.g., [12, 13, 14, 15, 8]). On similar grounds, Lopes and Bidarra [4] argue that the content of the game, the rules, the narrative, and the environment are mostly static, while the player who interacts with them is dynamic. This could lead to problems such as losing the motivation to continue playing, predictability, non-replayability, and repeatedly using a previously successful strategy. It has therefore been argued that considering the individual characteristics and the state of players can affect the effectiveness of the serious game (e.g., [16]). To cover the wide range of (slightly) different terms used in the literature (e.g., adaptation, adaptivity, personalization, customization) to convey this principle, we will use the term *individualization* when we do not want to make a distinction between the different terms and their different definitions.

For entertainment games, it is known that individual differences among players can influence the game experience (e.g., [17, 18]). Therefore, different types of players are recognized in the literature. For instance, one of most referred to categorization of player types is from Bartle [17] that considers players to be either "killers", "achievers", "socializers", or "explorers". However, the audience of a serious game is broader than that of an entertainment game; it includes also non-gamers. Therefore, taxonomies of player types developed for entertainment games to deal with individual differences are too limited to ensure adequate and effective individualization in a serious game, as the users of a serious game may also exhibit differences in terms of *learning style*, *intelligence types*, *anxiety*, *attention*, *engagement*, *task performance*, *knowledge level* and more, which are not all covered by existing player types. Exploiting these differences could aid designers and developers in crafting more engaging and effective serious games. This is opposed to the "one-size-fits-all" approach and is in general referred to as personalization or individualization. In the context of serious games, this concept refers to *tailoring the serious game to the individual's needs, states, abilities, and preferences*. Individualization can be achieved in different ways and at different stages of the life cycle of a serious game. Tailoring can be done in advance (during design), at the start of playing the game (often called static adaptation or static personalization), or completely dynamic while playing the game (often called adaptation).

In the domain of serious games, individualization can serve two interrelated purposes. First, it can improve players' game experience, and second, it can improve their task performance and/or knowledge acquisition. There are multiple factors that constitute the game experience of a player, among which the levels of experienced "flow state" and "immersion" are the most prominent and frequently used ones. The "flow state" [19] is defined as a state of absolute absorption to a task to a point of losing self-consciousness where the activity itself becomes rewarding on its own, and this enables an individual to function at her/his fullest capacity [20]. In the context of entertainment games, it is argued that the flow state can be achieved by providing a balance between challenge and the competence of the players [21, 22]. It has been stated that when experiencing the flow state, individuals work at their fullest capacity, including the capacity to learn [23, 24]. Immersion has also been claimed to positively affect learning. One of the most frequently used definitions for this concept was given by Murray [25]: *"the experience of being transported to an elaborately simulated place ..."* (ibid, Page 98). Dede [26] has argued that there are three ways in which immersion can enhance learning, which includes a change of perspective or frame of reference, situated learning, and facilitation of knowledge transfer to an authentic real-world context. These arguments strengthen the relationship between a good game experience and learning and support the idea of individualization in the context of serious games because it can positively affect the game experience of players and consequently their learning.

Considering the important role individualization can play in the effectiveness of serious games, the domain could benefit from a systematic overview of the literature on this topic. In this paper, we focus (as explained in section 2) on the aspect of the players that can be used to adapt a serious game to based on. The rest of this article is organized as follows. We start by elaborating on the objectives of this paper (section 2), followed by an overview of related work (section 3). Next, we discuss the different facets involved in individualization (section 4). In section 5, the methodology of the work is explained. Section 6 reports on the finding, which are discussed in section 7. The paper is then concluded in section 8.

2. Objectives

Numerous serious games have utilized individualization and extensive literature is available on this topic. Notwithstanding, systematic reviews of the literature that deals with the effectiveness of different individualization strategies in the context of serious games are scarce (see section 3). Our aim is to provide such a review. However, as we will explain in section 4, individualization is a complex process with different facets. Therefore, a systematic review covering all involved facets would be too great of an endeavour to fit into a single article. As such, we focus on an individual key facet, i.e., the *aspects of the player to adapt to.* These aspects are the characteristics of the players that could be used as input for the individualization process. In light of this, based on a systematic literature review (SLR) [27], we provide an overview of the aspects of players used for the purpose of individualization in the domain of serious games and indicate their merits in fulfilling the objectives of the individualization process in the different works. More precisely, our overarching goal is to investigate the question: *"which aspects of players for individualization are most frequently researched?"*. Consequently, the answer to this question will also aid in discussing the most frequently neglected player aspects as well. Furthermore, we will address the main limitations of the different research works that study individualization. Such a systematic literature overview will aid researchers and developers in understating why certain user aspects are more frequently used and studied, and which aspects need more research and evaluation.

3. Previous Research

Other researchers have performed reviews on individualization, while mostly focusing on what was individualized in a game and how it was done. Furthermore, none of these reviewers portrayed an overview of the effectiveness of individualization. Compared to other reviews in the domain, this paper focuses on works that detail the player aspects considered for individualization and for which an empirical evaluation for the effectiveness of the approach has been performed.

In 2011, Lopes and Bidarra published a review on adaptivity in games and simulations [4]. In this review, they looked at game adaptivity from an adaptation and generation perspective, i.e., their focus was on what to adapt and how to do the adaptation (methods). They touched upon player aspects to steer the adaptivity but did not consider them in detail. Moreover, in their work serious games are not explicitly targeted but also only considered. In 2012, Bakkes, Tan, & Pisan [28], provided an overview of the scientific literature on personalizing video games by using a player model. For this player model, they mention four applicable approaches: modelling actions, modelling tactics, modelling strategies, and modelling a player, but similar to the work of Lopes and Bidarra the focus of the review is on what to adapt and how to do the adaptation, described in the form of required and optional components. Moreover, the work of Bakkes et al. also does not focus on serious games. In 2004, Karpinskyj, Zambetta, & Cavedon [29] also surveyed works related to video game personalization, and they did focus on player aspects. They consider five categories: preferences, personality, experience, performance, and in-game behaviour. However, this review focused on video games in general, and therefore player aspect specifically relevant for serious games are not considered. Worth mentioning is that this review also points to the lack of empirical evaluations demonstrating the effectiveness or lack thereof of this approach. In 2016, Streicher & Smeddinck [30] provided a general state-of-the-art on personalized and adaptive serious games by means of examples rather than in the form of a systematic literature review. Pituba & Nakamura [31] in 2014 performed a systematic literature review to answer the question of what methods/strategies of adaptations are used for adaptive games. The scope was adaptive educational games and the period considered was 2009 to 2014. The descriptions of the works found by the SLR are very general and do not detail the specific player aspects used for the adaptations.

4. Individualization and Its Facets

A variety of terms fit under the umbrella of what we call individualization: adaptation, adaptivity, personalization, customization, and player-centered game design (note that we characterized the term individualization as tailoring the serious game to the individual's needs, state, abilities, and preferences). Over the years, different researchers have characterized these terms in their own way, and in more or less detail. For instance, *adaptation* was defined in [32] as a highly flexible environment where the differences of individuals are taken into account, and by Glahn [33] as changes in a system's look and behavior based on external factors. In [34], the term *adaptivity* is defined by Linssen as: *"an automated process in which something is able to alter itself in order to 'fit' into its surroundings"* (ibid, page 15), and in [4], by Lopes & Bidarra as dynamically adjusting game elements according to the individual performance of the player to make the game experience more unique and personal. *Personalization* is usually distinguished from adaptation by defining it as changes to a system's look and behavior based on a profile of the user. Glahn [33] states that personalization is a special form of adaptation. However, Göbel and colleagues [35] consider changes made to a system based on static information obtained from the user as personalization, while dynamically created information and changes during the gameplay as adaptation.

Streicher & Smeddinck [30], provide a good clarification of differences between the concepts and they give nuanced definitions. They define *adaptability* as *"the fact that a system is not fixed, but can be changed (to the needs of users, to changing environmental contexts, etc.; changes are usually understood to be performed manually)"*; and *adaptivity* as *"the fact that a system is not fixed, but dynamically changes over time (to adjust to the needs of users or an individual user, or to adjust to changing environmental contexts, etc.; typically happens automatically; often related to settings and parameters present in the given system)"* (ibid, page 344). Next, they also define the term *customization* and *personalization*. They define customization as *"the act of changing a system to the needs of a user group or individual user (manually or automatically; may or can be done by the group itself or by the user him or herself but may also be done by third parties; often related to the appearance or content of the given system"* and personalization as *"the act of changing a system to the needs of a specific individual user (often automatic but does not have to be, i.e., can be understood as a specific form of customization with a focus on individuality; personalization is also often related to appearance or content)"* (ibid, page 344). They see adaptability and adaptivity as means to realize personalization or customization.

Player-centered game design [36] on the other hand is different from adaptability and adaptivity. While in adaptability and adaptivity, a generic version of the game is changed based on information about the player(s), in player-centered game design, the game is designed for a specific group of people (called audience). This means that (in principle) no generic version of the game is created but the game is directly tailored to the target audience. Note that the term player-centered game design has also been used in the literature with a different semantic. In [37] for instance, player-centered game design is about catering adaptation to individual players. This may be a source of confusion. We define player-centered game design as *a game design paradigm by which different aspects of the game (e.g., game mechanics, narrative, interaction modality, etc.) are tailored to suit one or more groups of players that can be clustered based on a certain characteristic(s) (e.g.,* *playing style, personality, intelligence).* Player-centered game design is different from customization defined by Streicher & Smeddinck [30] because the system is not changed but designed based on the needs of a user group. These needs are established prior to the design of the game.

Note that the application of a combination of one or more of the previously explained concepts at the same time and inside a single game is possible. For example, a game can be designed for visually-spatially intelligent players [38] (using the player-centered design concept), and then, for instance, incorporate adaptivity (e.g., changing the difficulty of the game dynamically based on the player's performance). It is important to mention that although the presented concepts of individualization differ in purpose or approach, they all deal with the same issues, such as deciding which aspects of the user should be used for individualization, as well as which aspects of the system should be individualized and how. We call these issues "facets". We propose four facets, inspired by the works of Karagiannidis & Sampson [39] and Brusilovsky [40], fundamental to any individualization method:

1. What is the motivation for individualization? This facet is concerned with motivating the need for individualization. In short, in the context of serious games the motivation is mostly related to creating better gaming experience(s) and achieving the objective(s) of the serious game more effectively (as was elaborated on in section 1).

2. What aspects of the user are used for individualization? Numerous aspects of a user can be considered as inputs for individualization. Examples in the context of serious games are: *performance, prior knowledge, skill level, preferences, learning style, intelligence levels, physiological and psychological states.* These aspects can be measured either prior to using the game or in real-time. These aspects are usually grouped and maintained in a so-called *"user profile"*.

3. What aspects of the system are individualized? Numerous aspects of the system can be adapted for the purpose of individualization. In the context of serious games, and in addition to the individualization of the content and navigation (as classically done in e-learning systems) [41], a wide variety of game aspects including *difficulty level (challenges)*, *game objects & game world*, *narrative*, *NPC (non-player character) behavior*, *game AI (artificial intelligence)*, *interaction modality*, and *game mechanics*, can be considered.

4. How is the individualization realized? This facet is concerned with how the different aspects of a user can be used to individualize different aspects of the system. This is often done by so-called "adaptation rules". For instance, in the case of player-centered design, the "how" is about following rules (guidelines) that suggest certain game mechanics based on specific user characteristics. In the case of a dynamic adaptation on the other hand, adaptation rules could be defined and deployed on the fly based on real-time measurements of player profiles.

Note that the possibilities for the actual individualization of a serious game may depend on the purpose of the serious game, the game type and game mechanisms used, as well as the intended audience. Furthermore, what will be effective in one context may not be effective in another context. Results obtained for one application domain may not necessarily carry over to another domain. Therefore, we also mention the context of the studies in our systematic literature review.

5. Methodology

For conducting our systematic literature review (SLR), we followed the methodology of Kitchenham & Charters [27], who provided detailed guidelines for planning, conducting, and reporting systematic literature reviews, resulting in the following review protocol.

Review Protocol: The aim of the SLR is to provide an overview of aspects of players used for the purpose of individualization in the domain of serious games and indicate their merits in fulfilling the objectives of the individualization process for specific contexts. It is important to consider the context in which the effectiveness was investigated because, as already mentioned in section 3, what will be effective in one application domain may not be necessarily effective in another. Also, which aspects of the game are adapted and how the adaptation is realized are also important to be mentioned as this may impact the results.

There exist a large body of work on individualization of serious games. These works cover a wide spectrum of research topics from theoretical frameworks proposing novel approaches to individualization, to the realization of systems that incorporate individualization on some level and evaluating its effectiveness. Notwithstanding, while moving from the theoretical end of the spectrum to the practical end, comprehensive studies become scarcer. Given our aim, we excluded purely theoretical research works and focused on work that included some form of evaluation. Next to research papers that focused on serious, educational, learning, or edutainment games, we also considered research papers in the domain of digital games for entertainment of which the reported results were not yet covered by papers from the domain of serious games, and show potential applications in this domain. For retrieving the works, a number of digital libraries (ACM, IEEE, Science Direct, PsycINFO, Google Scholar, and Scopus) were considered. The search was limited to publications from 2007 to 2019 and we searched for terms for games with educational/serious purposes in combination with different variations of individualization. More precisely, the reviewed research works were retrieved based on the following search string :

("adaptive" OR "adaptation" OR "personalized" OR "personalization" OR "player-centered") AND ("educational game" OR "learning game" OR "serious game" OR "edutainment game" OR "game")

Using this search string, 166 research papers were retrieved. These papers were subjected to in-depth screening. Using an iterative process with three researchers, the following inclusion criteria were used to decide on the eligibility of a research paper to be included in the SLR: First, the paper must explicitly address individualization in (serious) games, as well as the player aspects used for it. Second, the paper must either directly provide empirical results on the effect of individualization. Following this inclusion protocol and based on the consensus of the researchers, 37 papers met our criteria and were included in the literature review.

From the selected papers, the following data was collected: title, authors, year of publication, the complete reference, if the paper was part of a large research project then also the name of this project, the user aspects considered for the individualization, suggested method(s) of measuring these user aspects, aspects of the game that were the subjects of the individualization, and for the experimental evaluation(s): type of game used, application area (i.e., domain of the characterizing goals, e.g., medical training), type(s) of effectiveness measured (e.g., game experience, learning effect), short description of the methodology used, results, and limitations (if any). In addition, noteworthy findings and remarks about the work were made.

6. Findings

For the selected works, the focus of the findings is on the player aspects considered and how those player aspects were measured, as well as on the empirical evaluation of the individualization. Because the individualization effectiveness may be influenced by different factors, we also indicate the application domain/educational topic of the game, what aspects of the game were individualized and if relevant how the individualization was done. This is done to put the results into context. However, we do not discuss in detail what was individualized and how the individualization was performed, as this is not the aim of this SLR. As indicated, the objective is to obtain an overview of *what aspects of players* have already been used for individualization and which were successfully/not successfully used in enhancing the game experience and/or learning outcome/task performance of players.

To provide a better overview, the findings are reported by grouping them into three categories based on the player aspects that they considered: *performance*, *physiological parameters and affective states*, and *personality traits*. The proposed three categories emerged from the reviewed papers by identifying the higher order type of player aspect they studied. To simplify the used terminology, we will use the terms "player" and "game" to refer to the user and system, respectively.

6.1. Player's Performance

Almost all individualization consider the performance of the player as one of the aspects to alter a game. The player's performance in the context of a game could range from referring to the execution of basic tasks in relation to the objectives of a game (e.g., removing all the blocks in a pong game), to physical performance (e.g., balancing in an exergame), over to higher level task executions that express knowledge acquisition or retention (e.g., performing the correct order of actions when doing a triage procedure). We identified in the reviewed works three main game aspects that are individualized based on performance: *difficulty*, *level/story*, and *feedback and intervention*, and grouped the discussion of the works accordingly to keep the overview.

6.1.1. Considering Performance for Dynamic Difficulty Adjustment (DDA)

Dynamically adjusting the difficulty level of a game based on the performance of the player has been widely applied in entertainment games as well as in learning games [30]. The goal is to provide the perfect balance between the player's level of competency and the level of challenge imposed by the game. Exergames as well as learning games usually employ such an approach.

Burke et al. [42] use a series of mini games for physical rehabilitation of stroke patients. A webcam tracks the arm movements of players while manipulating game objects. The games keep track of the player's in-game task performance to adjust the difficulty. The initial difficulty level is set by a therapist based on the impairment of the patient. A study with two phases was conducted. The first phase was with 10 able-bodied participants aiming to test the playability and to improve the game. The second phase was with three participants with disability caused by stroke. These participants could play each game as many times as desired, with each individual play session lasting 90 seconds. Both phases show positive results with respect to the playability and usability of the mini games. The disabled participants approved the adaptivity feature, but thought that the games were speeding up too quickly when they performed well, causing the game to become too difficult.

In a later work [13], Hocine et al. show that a game following the same principle (i.e., difficulty adjustment based on in-game performance), positively affects the training outcome of stroke patients. In this work, the adaptation is based on measuring the number of consecutive task successes and failures. In an experiment, each patient performed an assessment exercise and then play a randomly selected game version (there were three versions: dynamic difficulty adaptation, incremental difficulty adaptation, and without difficulty adaptation). Seven post stroke patients participated where each played with each version, once per day. The results show that the dynamic adaptation technique increased the number of tasks, number of successful tasks, as well as the movement amplitude during a game session. The differences were significantly more pronounced in the game with the dynamic difficulty adaptation strategy compared with the two other games.

Similarly, in [43] Smeddinck and colleagues describe an exergame for patients with Parkinson's disease that is using DDA to adapt the game in terms of speed, accuracy, and amplitude, based on the in-game performance of the player (the goal of the game was to collect stars). The game was tested with three patients over a period of three weeks based on game logs, observations, interviews, questionnaires, and therapists' analyses. The results indicated that the game was able to adapt to patients' capabilities, and evokes a good experience in them.

Goršič, Darzi, & Novak [44] compared different adaptation strategies for an arm rehabilitation pong game: an automatic adaptation based on the performance of the players, and a manual one (by the players themselves, e.g., changing the paddle size, or ball speed). Both versions were compared with a non-adaptive variant. First, the game was evaluated with 32 pairs of unimpaired participants who played the three variants of the game, each time for nine minutes. Then, the manual and automatic adaptations were also tested by five pairs consisting of a person with arm impairment and an unimpaired friend or relative. Participants' levels of motivation and experiences were measured with questionnaires and the results showed that the unimpaired participants experienced more motivation, enjoyment, effort, and pressure (necessary for the rehabilitation task) in the adaptive (automatic or manual) versions (automatic as well as manual) and preferred it over no adaptation. The impaired participants had a clear preference for automatic adaptation.

Afyouni, Einea, & Murad [45] proposed the use of a virtual coach (a rehab bot) in a virtual reality environment to help patients in performing different exercises correctly. The adaptation is based on input from a 3D motion capture sensor (Kinect Xbox One) and a virtual reality head-mounted display to track the patients movements. Accordingly, the level of difficulty is adjusted and alerting instructions are generated. In detail, response time, accuracy of posture, and joints' range of motion are used for adapting the difficulty of the exercises. The results of a pilot study with five patients and three therapists showed that the participants positively perceived the effectiveness of the proposed solution.

In [46] González-González et al. proposed TANGO:H, an adaptive gesture-based rehabilitation exergame to provide patients with adaptive exercises based on their interaction and on previously collected data about their skills. The adaptive system that recommends the appropriate exercises based on the player's skills and history was evaluated using a simulation. The effectiveness, efficacy, learnability, and satisfaction of the gesture-based interaction exercises were evaluated in a pilot study with six individuals with Down syndrome; three participants used the exergame and the other three used traditional paper-based exercises. Results were considered satisfactory indicating the adaptive exergame being better than traditional exercises.

The work of van Oostendorp and colleagues [47] is among the few that investigates the effect of DDA on learning outcome. The focus of the work is on dynamically changing the difficulty level of the game based on the in-game task performance of the player by varying the attributes of the NPCs when performing a medical triage procedure. An experiment comparing the adaptive version with a non-adaptive version was performed with 28 individuals of university-level education. The participants were randomly assigned to the adaptive game condition (n=14) and the control condition (n=14). Learning effect was measured using pre and post tests, and engagement via questionnaires. The results of this experiment indicate that the adaptation had no effect on the engagement of the players but significantly improved their learning outcome.

Belahbib et al. [48] present a learning game (focusing on teaching basic math equations to children) that adapts itself based on the performance of players using machine learning (by monitoring and evaluating the in-game performance of the player). Two versions of adaptation were compared with a non-adapted version in an experiment with three groups of players, each playing a different version. The authors have reported that the adapted game was more beneficial for the participants than the non-adapted version in terms of learning effectiveness. However it is not clear whether the difference was statistically significant.

Hendrix et al. [12] propose a six step plan for implementing DDA based on the player's performance. To validate this plan, they applied it to an existing mobile serious game called PEGASO focusing on guidance for optimizing lifestyle in teenagers. They did an evaluation with eight participants (friends and family). Each participant played both the original and the adapted versions, but the order with which they played varied. The main focus of the evaluation was to validate the plan and assess the preference for a version. The results showed that five participants preferred the adapted version and the remaining three had no preference. However, in general the ones that played the adapted version first performed worse than the one that played the original version first.

Hocine et al. [49] present a serious game to train children's attention skills. The game is using DDA based on an in-game assessment of their attention level, but a tutor can also update the difficulty. A pilot study was performed with 11 children to investigate the effect of adaptation on their game experience and performances measured using questionnaires and game logs. Most participants reported to have a good experience, but no results in terms of performance effectiveness was reported, as the game was not compared with a non-adapted version.

6.1.2. Considering Performance for Personalized Level/Story Generation

Dynamic level/story generation based on the performance aspect of players is in general less researched than difficulty adjustment.

In the *ELEKTRA* project [50, 5] and it successor, the *80Days* project [51, 52], the concept of Macro-Adaptivity deals (among other things) with story adaptation but the focus on the project and the evaluations was not on this aspect but on the Micro-Adaptivity, which we will discuss in the section 6.1.3.

In the *Siren* project [53, 54, 55, 56] a serious game about conflict resolution utilizing this strategy was developed. The Siren project uses a series of mini learning games, which are "adaptive" in the sense that the scenarios of the games are tailored to the player's profile. The level content is generated automatically and adapted based on the player's experience and behavior. In [54], a pilot study evaluating the approach is described. The study used a 3D single player mini-game where the player must distribute scare resources among NPCs and keep them happy. The game was monitoring and assessing the playing style of the players, focusing on their strategy for distributing resources fairly and cooperatively. Upon finishing a level, the game generated a new one automatically based on the game's prediction of the playing style as well as the experience of the players, with the objective of guiding the players to maximum fairness and cooperation. The results of the pilot study indicated that the average level of player cooperation had increased as the game progressed. However, there was no empirical evidence that the procedural content generation component was indeed responsible for this effect. In addition, the pilot study was done with participants not belonging to the target audience of the Siren game (i.e., being children between 10 and 12), but with six adults between 19 and 58 years old.

Xu et al. [57] present an approach for integrating Microsoft Kinect to provide patients with customized training materials depending on their real-time progress. The work proposes an algorithm based on Hidden Markov Model to generate customized training paths for each individual. The proposed approach was validated in a game targeted to children. Depending on both player performance and accuracy of progression, the game showed additional learning materials such as videos, more detailed text explanation, etc. An experiment with 10 children was performed. The participants were divided into two groups: one used the Kinect-based approach and the other used a classical video-based approach. They were given a series of simple and complex tasks to perform followed by five exercises. At the end, they were asked to fill in a short questionnaire. The results indicate that the proposed adaptive approach enhances the effect of the physical training by showing 10% improvement in accuracy.

Papadimitriou, Chrysafiadi, & Virvou [58] present FuzzEG, a game to help students learn HTML. The game uses Fuzzy sets to represent students' knowledge level, measured using quizzes. The game is adapted with the objective to provide students with different levels of difficulty for quizzes and different level of scenario details. A group of 60 students played the educational game for two weeks after attending classical lessons for one month. After that, they were asked to evaluate their experience using a questionnaire related to usability, likeability, educational effectiveness, and adaptivity. Results were very positive and encouraging: the use of fuzzy logic techniques seemed to be appropriate to reflect the player's knowledge level, and the adaptivity helped them with the learning.

6.1.3. Considering Performance for Feedback and Intervention

Individualizing the feedback and/or the intervention strategies in a game based on the performance of players is also a common approach. An example of such a strategy can be found in the well-known *ELEKTRA* project [50, 5] and it successor, the *80Days* project [51, 52]. Two different approaches of individualization are considered: *macro* and *micro adaptivity*. The micro approach

[5] is in the form of motivational interventions and cognitive hints given to the player and the macro approach is about the adjustment of the story pace and construction [52]. The process of individualization in the 80Days project goes beyond adaptive hints and interventions (also story adaptation is used as indicated in section 6.1.2), but together with ELEKTRA it is among the first researches on providing adaptive feedback and interventions in the context of learning games.

In [5], this micro adaptation is defined as *"an approach to non-invasive assessment of knowledge and learning progress in the open virtual worlds of computer games and a corresponding adaptation by personalized psycho-pedagogical interventions"* (Page 3). According to the authors, one way to guide and support the learners in the process of acquiring knowledge is to intervene when misconceptions happen or provide hints and feedback when the learning progress is unsatisfactory. To be able to achieve this, one should be able to measure the knowledge of the players, monitor their cognitive states (motivation, attention, etc.), understand possible misconceptions or unsuccessful problem-solving strategies they used, and more. In serious games, such assessments need to be done in a non-invasive manner in order not to impair immersion [50]. This approach was evaluated with the ELEKTRA game (teaching optics in physics) [59] with 40 school children. Compatible pairs of participants were used (one receiving adaptive feedback, the other not). The participants' learning outcome was measured with a post test. The results showed that the tailored interventions caused higher learning performance and a higher level of immersion compared to inappropriate or no interventions.

The 80Days game, using the micro and macro adaptivity, was evaluated using 16 school boys paired up to play the game [60]. Learning outcome was measured using pre- and post questionnaires. Furthermore, gaming experiences and usability were evaluated with intensive in-situ observations and interviews; content analysis of the transcribed audio data was supplemented by video analysis. The results indicated that playing the adaptative game could be beneficial for learning by playing, but there was no control group to justify this finding.

In [61], the ALIGN system (Adaptive Learning In Games through Non-invasion) is introduced, that implements an innovative, generic and reusable architecture for adaptive educational game development. The ALIGN system was demonstrated with different games, e.g., with the ELEKTRA game by in [61] and with the Language Trap game, an online causal educational game developed for Irish secondary school students to learn German, in [15]. For the Language Trap game, four types of adaptation were supported: *adaptive dialogue difficulty*, *performance feedback*, *motivational*, and *meta-cognitive hints*. The game was evaluated with 83 students who were randomly assigned to either a basic adaptation or an advanced adaptation groups. Learning impact was measured using pre- and post tests. The advanced adaptation group showed greater average learning improvement over the basic group, but this result was not statistically significant. The advanced adaptation group felt the presented dialogues had a more suitable difficulty compared to the basic adaptation group and this result was statistically significant. The advanced adaptation also had a positive impact on students' immersion, but this result was not statistically significant.

The work presented by Conati & Manske [62] evaluates the impact of *adaptive feedback* in a learning game, called *Prime Climb*, that teaches number factorization. The study was conducted in two local elementary schools with 44 sixth grade students who were randomly assigned to one of three conditions: a game with no form of adaptive support (13 students); a game with a pedagogical agent using a preliminary version of the student model (profile based on performance) (14 students); and a game with the pedagogical agent and a more accurate version of the student model (17 students). Pre- and post tests were used to measure the learning effect. However, no difference in learning was observed across the three conditions. The authors investigated possible explanations, suggesting that students may resent being interrupted often during gameplay, even when most interruptions are justified. As such, they state that *"achieving a trade-off between maintaining engagement and promoting maximum learning"* is important when using adaptive feedback.

In the context of the InLife project, Semet and colleagues [63] proposed the use of Ant Colony Optimization algorithm for providing rewards in an adaptive way in serious games. The used principles are that more rewards should go to poorly successful players, more rewards should go to poorly undertaken actions, and it is pointless to spend rewards on already successful players or actions. The system was deployed in four distinct pilot sites in Spain, France and Greece, but the duration of the project did not allow for acquiring statistically significant results regarding the effect of the algorithm. However, an in-lab experiment with a multi-agent simulator (based on comparing the proposed adaptive reward algorithm with a naive static strategy) was performed and confirmed the expected qualities of the use of an ant-based reward algorithm: scalable and providing dynamic "controllers" that can be conveniently used in real-time .

6.2. Player's Physiological Parameters and Affective States

The different affective states players experience while playing a game are considered by some researchers as aspects of a player that can be used in the process of individualization. These states, including *anxiety and stress*, *attention*, *engagement*, and *emotions* can be derived from different physiological signals and parameters, such as *heart rate*, *breathing*, *head motions*, and *facial expressions*. Physiological parameters and affective states are among the more recently considered player aspects for individualization and are hence less researched. However, different researchers have addressed their potential as effective contributing factors to better game experience and higher learning outcome. In the following sub-sections, we review research works in this context. We grouped the work into those considering anxiety and stress; those considering attention, engagement, and emotions; and those using the physiological parameters: heart rate and breathing as aspects of players for individualization.

6.2.1. Anxiety and Stress

Players experience different levels of anxiety and stress while playing. Depending on the goal of the game and the effect it attempts to have on players, these states can be measured and used as inputs for individualization. In [64], Liu and colleagues have show cased an individualization based on these factors for two entertainment games. Although this work is not in the context of serious games, we consider it here because to the best of our knowledge, this work is the first that measures anxiety and use the level of anxiety as a factor to dynamically change the difficulty level of a game. In one of the performed experiments, two version of a *Pong Game* both with dynamic difficulty adjustment mechanism (one based on performance, and the other based on the anxiety level of the player) were played in two sessions by 9 participants. In one session, the game difficulty was simply adjusted based on the in-game performance of the player, without considering their anxiety level. In the other session, the anxiety levels of the player were detected via sensors using a *Biopac system* and synchronized with game events. The difficulty of the game was changed in real-time based on the detected anxiety levels, without considering the in-game performance of the players. To avoid bias, the two Pong versions were played with an interval of at least 10 days and the order was randomized. Anxiety as well as challenge were measured using self-reporting questionnaires. The results of the experiments show that for seven out of the nine participants, dynamic difficulty adjustment based on the anxiety level has led to a more challenging game, and at the same time improved their in-game performance compared to the dynamic difficulty adjustment version based on performance.

Furthermore, and also not in the context of serious games, the work of Yun and colleagues [65] used a novel approach to individualization by using the facial physiology of the players to dynamically adapt the difficulty level of the game. The approach monitors the stress levels of the players using a thermal imaging system, *StressCam*. In an experiment, the difficulty level of a commercial shooting game, *Robot Game*, was adapted based on the stress level of the player. A total of 14 participants played the game in three modes: easy, difficult, and auto-difficulty. The results of the experiment show that this individualization approach led to a better gaming experience and the auto-difficulty mode outperformed the other modes.

6.2.2. Heart Rate and Breathing

The heart rate variability and the breathing pattern of the players are also aspects of the player that can be used for individualization. Several researches have used these factors.

In [35] Göbel et al. used the static information about the players (e.g., training plans and player model) for personalization, and vital parameters of the players (*speed, revolutions per minute, watt and heart rate, and activities and movements*) for dynamic adaptation of exergames. Technical feasibility and focus group studies with a limited number of participants (26 in total), showed potential for motivating people to exercise. This exploratory work was further elaborated in by Hardy et al. [66], where the authors propose an approach towards adaptive, long term motivating and physically demanding exergames for indoor training, composed of three components: application-specific hardware, software, and the human psychology and physiology. With respect to individualization, the gaming and training modules and the psychology (effectiveness and attractiveness modules) can be changed while playing, however, the hardware component as well as the physiological characteristics of the players cannot. An example of the use of a physiological aspect for adaptation would be the use of an ergometer bike with adjustable resistance, so that the game can be adapted based on the player's heart rate. In order to evaluate the effectiveness of the proposed components, a prototype called *ErgoActive* was used that included three mini-games. An example of such a mini-game was *Ergo Balance*, which is a combination of *Shoot'Em Up* and *Skill Game*. The objective of the game is to keep a clown balanced on a ball. For this, the player should maintain a fixed level of heart rate, speed and cadence. If the player cycles too slow or too fast, the clown will fall. At the same time, the player needs to click on the balloons with a mouse in order to gain points. The prototype was evaluated with 48 participants. Self-reporting of their fitness was used to set the initial power of the ergometer. Each participant played the three mini-games. The effect on the player's motivation was depending on the gender of the participants and their estimated fitness. The games were rated as motivating by the participants for both, short and long term motivation.

Furthermore, also the breathing patterns of the players can be used for individualization. The game *Chill-Out*, presented by Parnandi et al. in [67] uses breathing as physiological parameter for individualization. It is an adaptive biofeedback game that teaches its players relaxation by monitoring their breathing rate. An adapted version of the *frozen bubble* game, where the player shoots bubbles with different colors to eliminate them before the ceiling collapses, was used. If the breathing rate crossed the threshold, the auto shooting frequency was increased, making the game more difficult. Therefore, the player must maintain a slow and sustained breathing pattern. The approach was evaluated with 9 participants. The relaxation skills of the participants were measured by pre- and post tests. The participants were randomly assigned to one of three groups: a group that played the biofeedback game, a baseline group that performed deep breathing, and a control group that played the original Frozen Bubble game without adaptation or respiratory feedback. The results show that the adaptive version of the game with biofeedback led to the most effective results in terms of transferring the breathing skills to another stress inducing task, as well as to significantly lower arousal levels. This study not only shows that breathing rates can be use to control a game but also that, as opposed to the old belief that a quiet and peaceful environment is a necessity for controlling and reducing stress, games can be used as an effective tool to learn to control stress.

6.2.3. Attention, Engagement, and Emotions

There is a variety of information that can be extracted from facial expressions, eye gazing, head movements and other behaviors of the players while playing a game. This information can be used to measure attention, engagement, and emotional states. Although a few research works studying these aspects of players for individualization can be found in the literature, their applications in serious domains remain largely unexplored.

In the context of the Siren project, introduced earlier (section 6.1.2), individualization based on affective states was also considered. In [56], Karpouzis and colleagues explain the approach taken but did not report any evaluation results. The *emotions and attention* of the players were assessed via video feed from a web camera mounted on top of the player's screen [68]. The combination of the detected states and the in-game behavior and performance of the players were mapped to the flow diagram of Csikszentmihalyi. The proposed approach is that if the game determines that the player is bored, it will produce a more difficult instance of the game to balance challenge and competence. Definitions and interpretations of different gazing behaviours, facial expressions, and head poses, as indicators for player attentiveness, were based on the analysis of the Siren gameplay database [69]. Once the game is over, the user model that constitutes the affective and behavioral indicators, will be used to generate a relevant and interesting instance of the next game (the games are procedurally generated [70]) based on the predicted levels of challenge and frustration. The work Asteriadis et al. [69] deals with the use of the *head movement* of the player as an indicator of the their *frustration* and *engagement*, as well as the degree of *challenge* imposed by the game. Based on the methodology introduced in [68], the head movements of the players (average head motion per game, head motion when player loses, head motion at stomping on an enemy to kill him, and head motion when player is about to make a critical move) that are recorded during their gameplay sessions (while playing Infinite Mario Bros) were extracted, analyzed and classified as either, challenged-not, challenged, engaged-not, engaged, and frustrated-not, frustrated. The preliminary results of this work indicate that head motions can be used during gameplay with the objective of assessing hidden information regarding the different states of the players. It was observed that different players pose differently, and according to the authors, this triggers the idea of building profiles for individualization purposes. Notwithstanding, no empirical evaluations for the applicability of this approach in the individualization of (serious) games was reported.

In [71], Chanel and colleagues maintain the player's *engagement* to a game (Tetris) by monitoring players' (20 in total) emotional state, and then changing the game difficulty accordingly. Before commencing the experiment, each participant played the game several times in order to determine the game level they reported to be engaging. This was used as the point of reference for the participants' skill level. Then, depending on the skill level of the player, three experimental conditions were determined: medium condition (game difficulty equal to the skill level), easy condition (lower difficulty than the player's skill level), and hard condition (higher difficulty than the player's skill level). During the sessions, participants were equipped with several sensors: GSR (Galvanic Skin Response) to measure skin resistance, plethysmograph to measure relative blood pleasure, respiration belt to estimate abdomen extension, and a temperature sensor to measure palmar temperature changes. Furthermore, EEG was used to measure the task engagement, but its analysis was not part of the experiment. Twenty-three participants played 6 sessions (5 minutes each, 2 sessions for each of the three conditions) of Tetris. The objective of participants was to obtain the highest score. After each session, a questionnaire about the emotions felt and the level of involvement in the game was administered. The result indicated that playing a Tetris game with the mentioned three different levels of difficulty evoked different emotional states that could be identified as boredom, engagement and anxiety. Furthermore, it was observed that at least two of these states could be, with a reasonable accuracy, detected from physiological signals. Moreover, it was established that players' level of engagement could decrease if the game difficulty did not change effectively with respect to their skill. These results show that affective states of the players could be used as a factor for game difficulty adaptation. Moreover, in [72] the researchers have complemented this study with the results of EEG (from the same dataset used for the previous work). They denote that the use of EEG for measuring emotion is a more robust approach to detect the short-term emotions of players.

Apart from engagement, *attention* level of players is another aspect that has been deemed important by many researchers. However there is little work on using attention for the process of individualization. In [73], Muir & Conati present a user study that investigates what factors affect the attention of students to user-adaptive hints while interacting with an educational game, *Prime Climb*, that teaches number factorization. As part of the adaptation, individualized hints are given to the players. In order to capture and analyze player's attention to the adaptive-hints, *eye-tracking* was used. The results of the study (with 12 participants) indicated that the eye movement patterns are affected by factors including existing user knowledge, hint timing, and attitude toward getting help. This result could be used to make the hint delivery individualized based on these factors. A pre-test was used to measure the participant's level of knowledge about number factorization. Then the calibration phase of the eye-tracker for the Tobii[1] device was performed. Next, each participant played the game with an experimenter as partner. Afterwards, the participants took a post-test equivalent to the pre-test and completed a game experience questionnaire. In order to analyze the attention of the participants to the adaptive hints, an area of interest (AOI) was defined that

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

covered the text of the hint message. Furthermore, two eye gazing metrics were used to measure attention: *total fixation time* and *ratio of fixation per word*. The total fixation time is "the total time a student's gaze rested on the Hint AOI of each displayed hint", which is considered as a measure of overall attention. The ratio of fixations per word was considered as a measure of how carefully a student scans a hint. The results of the experiment show that there was no improvement from pre to post-test performance. Each factor (Time of Hint, Hint Type, Attitude, Move Correctness and Pre-test Scores) to some extent affected the attention to the hints. Furthermore, it was observed that attention to hints decreased as the game proceeded, and the highest level of attention drop was for hints about definitions (definition of rules, theorems, principles, etc.), suggesting that these kinds of hints are not perceived well. In terms of attitude, it was observed that low attention for those with the attitude of not wanting help, and higher attention for those with the attitude of wanting help was the case. This indicates that the player's attitude plays a bold role in adaptive hints. In terms of game performance, it appears that when students paid attention to the hints, they made fewer errors on subsequent moves. This result may suggest that future investigation on how to increase player's attention to the hints might be useful because it can improve their performance and possibly their learning outcome.

In a study by Alves et al. [74], two adaptive versions of a first-person shooter game are compared. The first version was adapted based on player's mental state (anxiety, boredom, flow), and the second version solely based on player performance. The mental state of the player was measured by means of their heart rate and the beta band of their brainwaves. An evaluation was done with 21 participants comparing their self-perceived flow and in-game score across the different adapted versions of the game. The results of the evaluation showed that the version adapted based on the performance of players caused a better game experience than the one adapted based on their mental state, which was opposite to what was expected.

6.3. Personal Traits

Characteristics such as *personality*, *preferences*, *play style*, *learning style*, and *types of intelligence* are also aspects of the player that can be utilized in an individualization process.

The work Hwang et al. [9] proposes a personalized game-based learning approach based on the *sequential/global dimension of the Felder Silverman learning style theory*[2] [75]. The individualiza-

[2]According to Felder and Silverman *"a learning-style model classifies students according to where they fit on a*

tion takes place based on the way a role-playing (RPG) game is presented to the player as well as the way the player navigates the game (either sequential, guiding the player step-by-step; or global, allowing the player to "jump" to a mission/scene they want). Based on a between-subject design experiment with 46 students, it was shown that the personalized version of the game based on the learning style of players caused a significantly higher levels of learning motivation and outcome compared to a non-personalized version.

Soflano, Connolly & Hainey [76], also presented a research work which investigates tailoring learning content based on students' learning style according to the Felder Silverman theory. To do so, three game modes of a 3D Role-Playing-Game were developed: a non adaptive game mode, an adaptive game mode based on the results of a questionnaire (Felder-Silverman learning style questionnaire) to identify students learning style, and an in-game adaptive mode based on students' interactions. The game recorded and analyzed students' interactions with game content to predict their learning style. Next, an experiment was conducted to compare the learning effectiveness between the three modes of the game, and with paper-based learning (textbook learning). The study was performed with 120 higher education students to learn Structured Query Language (SQL). The participants voluntarily participated and had no knowledge of SQL. There were 78 participants from computing programs from different universities. The rest were from different programs such as mathematics, law, psychology, accounting, etc. The learning of the participants was measured using pre and post-knowledge tests. Students who learned from the game showed significantly higher learning outcomes than the ones who learned from textbook. Secondly, the adaptive versions resulted in the highest learning outcome and allowed students to complete their tasks faster than the other two versions, however, there was no difference between the two adaptive versions.

On similar grounds, in the work of Lindberg & Laine [10] the individualization was based on both player type and learning styles that separately affected the learning content of a 2D action-puzzle serious game called *Minerva* focused on teaching programming to children. The learning style of players were measured based on the Honey and Mumford's Learning Style Questionnaire [77] (using four styles: Activist, Reflector, Theorist, and Pragmatist) and affected how the learning

number of scales pertaining to the ways they receive and process information" (Page 3) [75]. The style of a person can be then defined on four dimensions of: active-reflective, sensing-intuitive, visual-verbal, and sequential-global.

material was displayed to the leaner in the form of personalized game instances (i.e., different orders of video, images, game, and text material). The player style was measured based on Bartle's player types [17] (Killer, Achiever, Socializer, and Explorer) and affected the game experience of players by personalizing the mechanics of the game to suit the style of the player (e.g., more monsters to shoot for killer types). Moreover, based on his/her player type, the game awards the actions of the player differently (e.g., talking with NPCs will add points to the socializer types), which is labeled by the authors as dynamic adaptation. The player type could be changed during the gameplay, whereas learning style could not. The study focused more on retention and engagement and less on the adaptive features as a whole. Based on a mixed-method evaluation using a between-subject design with 64 students comparing the individualized game with classical methods for teaching programming, the game showed tentative promise in being more engaging to the students, but no significant differences in the retention of students. However, the individualization feature of the game itself was not compared to a non-individualized version.

The *"Theory of Multiple Intelligence"* (MI)[3] [38] has also received attention in serious games. In [78, 79], Sajjadi et al. have created games targeting specific types of intelligence profiles of players. These games included a number of game mechanics that were determined to be recommendable for the intelligence dimensions targeted by the games. This was based on the evidence-based mappings between the theory of MI and game mechanics introduced in [80, 81]. In [78], a non-serious game targeting bodily-kinesthetically intelligent players (measured through self-assessed questionnaires) was introduced and evaluated. The evaluation of this game with 22 participants has revealed that the targeted audience of this game indeed had significantly better game experience in terms of competence and immersion, and at the same time lower level of tension and negative affect. These results were confirmed by a second study on another game in [79, 82] which targeted logically-mathematically intelligent players (measured through self-assessed questionnaires), with the objective of developing competencies for understanding and remembering the truth tables of proposition logic. A pilot study was conducted with four participants for measuring the learning outcome and with 11 participants for the game experience. Pre and post tests were used to measure

[3]The term intelligence is defined by Garner as *"the ability to solve problems, or to create products, that are valued within one or more cultural settings"* (Page 28) [38]. In light of this, he has proposed eight dimensions of intelligences possessed by everyone, but to different degrees. These dimensions are: visual-spatial, bodily-kinesthetic, musical-rhythmic, linguistic, logical-mathematical, interpersonal, intrapersonal and naturalistic.

the effect of game on the learning outcome, and the post-game experience questionnaire (GEQ) was used to measure the game experience. The results of a pilot study showed that the targeted audience of this game was having a significantly better game experience in terms of exhibiting higher levels of immersion, flow, and competence. Furthermore, the results of a pilot study on learning showed that the targeted audience showed improvements in their post knowledge test.

Out of the studies we surveyed, three focused on the use of the personality of the players. The work Shabihi et al. [83] used Keirsey's temperament theory [84] to group players based on their values for the Myers-Briggs Type Indicator (MBTI) scales [85]. Their study (between-subject) with 29 participants measured learning outcome and engagement for a serious game aimed at teaching vocabulary with an adaptive mode and a non-adaptive mode based on various game elements such as points, leaderboard, feedback, etc. The results showed a significant difference between the adapted and the non-adapted mode for engagement, but no significant difference for learning outcome. Another study [86] focused on introvert vs. extrovert personality types, based on the Big Five taxonomy [87]. In this work, the personality types, level of motivation, cognitive load, and acceptance were all measured via questionnaires. The results of the experimental group were compared to the results of a control group who played a non-personalized version of a serious game aimed at teaching computer science and Internet concepts. The game was personalized to introvert and extrovert players by providing different mechanism in which the learning content was presented to them in light of the learning strategy (reflective learning for introverts and active learning for extroverts) and mechanics of gameplay (awards for introvert, and NPCs and emenies for extroverts). An experiment with 51 participants showed that both personalized and non-personalized conditions caused nearly identical levels of motivation. The personalized condition yielded better results when comparing the cognitive load of the players. Regarding usefulness, ease of use and intention to use, there were only significant differences in the usefulness and in the intention to use, where the personalized condition resulted in higher values.

Ku et al. [88] looked at cognitive styles, focusing on serialists vs. holists. The performed studies (two, each with 60 participants) had the aim to compare (automatically) personalized games with versions that could be manually customized by the players. Three puzzle-solving mini-games focusing on reasoning, logical/mathematical, and strategic thinking abilities were used in this research. To measure Holist and Serialist biases, an existing questionnaire was used. In one study, participants could customize some of the mechanics of the game (narrative, hints, and music) based on their preference, while in the second study, personalized versions of the games were given to players based on their cognitive styles and findings from the first study. The authors used pre and post tests to measure learning performance, and a questionnaires to measure game perception. The results showed that both versions resulted in increased learning, but overall players felt more positive about the version of the game that they could customize personally. Furthermore, holists might not always favor to listen to music because they frequently switched the music on/off. On the other hand, serialists did not prefer to use hints.

6.4. Personal Data

Players' personal data has become a valuable commodity in online advertisement, but it can also be used to individualize the game content, as shown by Xu et al. [89]. For this study, players were requested to log content (images & video) of their daily life for a period of three months. The authors then converted this data to a personalized game experience where the images generated from the player's collected data are integrated into the game (eight puzzle serious games focusing on training memory, attention, speed, vision-spatial, and executive functioning). Game data from 26 participants were collected, analyzed and compared with a generic version of the game without personalized content (the contents of the puzzle challenges - four personalized and four generic puzzles). Results showed a higher adherence (number of sessions playing a game) to play the personalized version and a higher enjoyment. For other preference measures (i.e., overall preference, content preference, and game mechanism preference), as well as cognitive functioning no differences were observed. There was also a discrepancy between the results for the different mini-games used, suggesting that other factors (e.g., image quality, game difficulty) beyond game content should be considered in the future.

7. Discussion

As our review shows, a wide range of different aspects of players have already been investigated for the purpose of individualization. Tables 1, 2, and 3 provide a summary of the reviewed researches using performance, physiological parameters & affective states, and personal traits player aspects respectively. These tables only show the works that reported some form of empirical evaluation; works without an evaluation are left out as we have opted to provide an overview of empirical evidence for the different aspects of players used for individualization found in the literature. Note that some of the works did not conduct a true empirical evaluation but rather performed a simulated experiment. We also have mentioned these in our overview tables, but indicated this in the limitations.

The last column of the tables provides the reference to the research work reported in a row. The tables provide the player aspects that the works consider (first column), the variety of instrument(s) used for measuring the player aspect(s) (second column), the effect(s) intended with the individualization (e.g., learning outcome, game experience) (column three), and the aspects of the game that were adapted (column four). In the "Methodology" column a short description of the methodology used for the evaluation is provided (a more elaborated description is given in the section 6). The column "Results" summarizes the findings reported by the work, and in the column "Limitations", we provide the major limitations of the work. The next column indicates the type and the application area of the game used in the evaluation, and the column "Year" gives the year in which the work was published.

In the following sub sections, we first discuss our general findings. Next, we discuss limitations of the reviewed research works, as well as the limitations of our SLR.

7.1. Trends

Our work highlights that many different aspects of players have already been investigated in the context of serious game individualization. Fifty percent of the reviewed works (18 out of 36) consider the player's performance for adapting a game. If we take a closer look at this aspect, we see that the in-game performance (7 papers) and task skill (7 papers) have been extensively researched in terms of their effect when used in individualization. Player behavior (2 papers) and knowledge level (2 papers) are used to a lesser extent; while preference, learning progress, player experience, and attention were considered sparingly (each 1 paper). We suspect this is because it is not easy to measure these aspects in an accurate way, especially during the game play and solely based on player actions.

Nine works considered factors related to physiological parameters and affective states for the individualization. We see that affective state & physiological state (2 papers), together with watt & heart rate (2 papers), speed (2 papers), and anxiety (2 papers) were considered slightly more than flow, boredom, stress, attention through eye tracking, and breathing rate (1 paper) (however, note that we are comparing small numbers). Cadence, revolution per minute, and speed are also not used often (each 1 paper), but these are player aspects which are quite application dependent (mostly applicable in some types of exergames).

For the use of personal traits (nine works in total), we see that learning style (3 papers), personality (2 papers), and multiple intelligence (2 papers) were considered more than aspects such as cognitive style, playing style, and personal data (each 1 paper). But again the numbers are small and so are the differences.

Note that the distributions over the specific aspects should only be considered as an indication of how often the aspects are used, because the aspects in the used terms may overlap and the granularity is not always the same. For instance, Multiple Intelligence may also be considered as a cognitive style. Our report is based on the terminology used in the reviewed papers, which does not appear to be uniform; analysing and discussing the overlap between the terms or defining a disjoint set of term is not in the scope of this paper.

Based on these distributions, we see that the majority of research works have focused on the one hand on performance, which is in general easier and less intrusive to measure during game play than for instance affective states, and on the other hand on player aspects which can be measured or collected prior to playing the game, such as learning style. Player aspects which are (currently) hard to measure in an objective way are less considered. This observation can be interpreted as follows. If it is not possible to measure the player aspect in a reliable and non-intrusive way, it may not be practical to use it for the adaptation. On the other hand, dynamic aspects (e.g, attention, stress), if measured reliably, can provide rich real-time information about the state of learners in relation to what they are experiencing in a game. Such information can help in realizing adaptive strategies that base themselves on the emotions of players rather than their task skills and immediate performance fluency.

In Figure 1, we show the evolution of the number of papers in the three major categories over time, which further illustrates the wide adoption of performance as a player aspect, and lesser focus on affective and physiological states. Furthermore, we have noticed that certain player aspects are generally neglected in the literature, for instance, aspects related to Head-Mounted Displays (HMDs) for Virtual Reality (VR) applications such as head (and controllers) rotation and translation (in 6 degrees of freedom). Nevertheless, these information, when monitored in real-time, could provide meaningful insights on where in the virtual environment a player is paying attention to and what physical actions they are performing. In the context of exergames for instance, these information could be part of user performance for dynamic difficulty adjustment. An other example is the surroundings of the player. This could be particularly relevant in the context of Augmented Reality (AR) games, where the reality of players is augment with virtual objects. Consider an AR serious game about botany where the players can use their smartphones to scan plants in their physical surrounding to learn about them and discover the ones they do not already know. Depending on which plants are available in the surroundings of a player (can be scanned by them), the game can adapt its content and provide context-relevant challenges to the players. A slightly different user aspect is the Geo-location coordinates of players. Similar to techniques for website localization, this information can be used for the automatic content adaptation of a game based on the Geo-location of players. For instance, in a game about cultural assimilation, the learning content for teaching people how to behave in different social situations in another culture (e.g., while traveling in Japan) can be adapted based on whether the player is shopping, at a restaurant, museum, etc. Lastly, we see a general lack of user data fusion in the literature. Rarely user data from different categories (or multiple from within one category) are fused together to derive the current state of the user. As an example, consider user interaction with anthropomorphic entities such as Embodied Conversational Agents (ECA) for social skills training [90]. The behavior of the ECA is this domain is determined based on the actions of the learners defined by verbal, non-, and para-verbal behaviors. For instance, if the learner utters an out of context and inappropriate sentence to the ECA, the ECA is expected to adapt accordingly and respond in an educationally adequate way. However, the learner can utter a seemingly appropriate content but with a very condescending tone combined with an inappropriate body language. In such a scenario, the system should fuse body tracking, voice intonation, and speech content data of the user to arrive at a single state representing their emotional intent. Data fusion is a very complex task, but an extremely powerful method for rich individualization. The mentioned was merely one example of how fusion of player aspects can be used to create a "user state" with a different semantic than the individual aspects. With the help of computationally powerful methods such as Machine Learning (ML), a wide variety of player aspects can be fused and models can be trained to extract relevant "features" from player data.

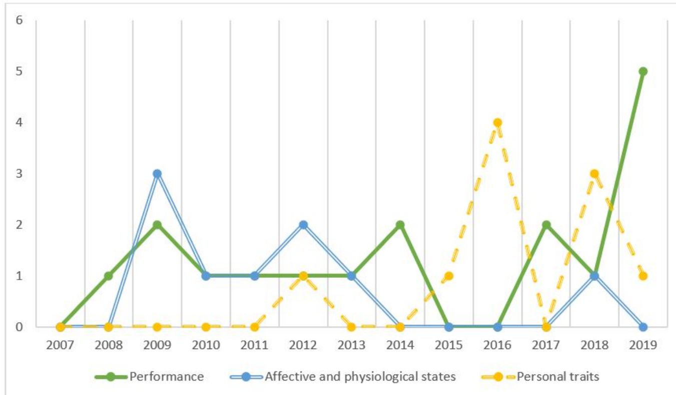

Figure 1: Trends of Player Aspects Over the Years

With respect to the "measurement method" used for assessing the aspect(s) of players, we see that game logs, self-reported questionnaires, and in some cases peripheral devices such as sensors are the dominant methods. When reflecting on this observation, we notice that using methods such as ML for observing, evaluating, and profiling players based on their individual characteristics are not widely used in adaptive serious gaming domain; only in recent years we see that researchers are considering to use them. As they show, utilization of trained computational algorithms can prove to be an invaluable asset in accurate detection of one or several player aspects at the same time. Given the growing interest in and application of Computational Data Science and Artificial Intelligence, we expect to see a trend in the use of more advanced mechanisms for player profiling in the future.

Furthermore, many of the reviewed works (29%) focus on the effect(s) individualization may have on the game experience (or an aspect of it) of the players. This confirms a general belief among researchers that a good game experience is an important requirement for achieving a high task performance or learning outcome. Notwithstanding, a high percentage (38%) of the reviewed works focused on learning/training outcome as the effect of the individualizing strategy they employed. In addition, nearly 33% targeted aspects such as motivation, game performance, usability, user adherence and cognitive load.

We also see that the most common aspects of games subjected to individualization in our review are the difficulty (19 papers), feedback & hints (9 papers), game mechanics (5 papers), and interface/learning content (5 papers). Games aspects such as narrative (2 papers), and content (image, video), and environmental settings (1 paper each) are used to a lesser extent. Despite the fact that games are a much richer medium compared to conventional e-learning systems, we notice that typical aspects of games, such as narrative, music, social companions/conversational agents, NPC behaviors, and interaction modalities are generally neglected for individualization.

Furthermore, our review shows that exergames are by far the most commonly used theme for individualized serious games (9 papers). As individualization can be directly tied to the physical fitness/rehabilitation of users through dynamic difficulty adjustments for instance, there is no surprise that exergames are the topic of many research works. Next to this, we see that game topics such as math, logical thinking, and strategies skills are also among the popular ones in this domain (5 papers). Quite a few interested research works (6 papers) have implemented and evaluated individualized strategies, but not in the context of a serious game. This could be attribute to the complexities involved in the design and implementation of a game from scratch, in addition to the sophistication involved in the design of a serious game where the pedagogical strategies and mechanics of gameplay are well integrated into a unified experience. Serious games with topics such as computer science (3 papers), language learning (2 papers) and behavior change, natural sciences, relation, lifestyle, geography, physics, conflict resolution, and medical triage (1 paper each) are also used for individualization, but to a much lesser extent.

7.2. Limitations of the Works

While the reported results are mostly positive in term of one or more aspects of the effectiveness of individualization, the evaluations often have limitations. In general, the sample sizes are often small (18 papers) and the experiments are run over a short period in time (which usually appeared together). Furthermore, we observed that in quite a few cases, the proposed individualized approach is not methodically compared against a non-individualized one as a control condition (13 papers). Sometimes, the design of the experiment (e.g., only immediate and short term evaluation of effectiveness, use of subjective methods such as questionnaires for measuring player aspects (4 papers)) or the targeted sample (e.g., highly homogeneous and partially biased audience (3 papers)) were inadequate or detailed information was lacking (2 papers). The combination of these limitations impedes from drawing, with a high level of certainty, conclusions regarding the effectiveness of individualization. In addition, when drawing conclusions, the empirical results should also be considered in the context of how the individualization was performed, i.e., which aspects of the game were adapted and how.

Furthermore, it is important to note that although some of the reviewed research works have demonstrated the effectiveness of individualization on learning/task performance, it is still an open question whether individualization can in general benefits all types of games and for all serious purposes. This further corroborates the necessity for more empirical research, and in particular longitudinal studies on this topic.

Although the focus of this paper is on serious games, we found quite a few research endeavours that concentrated their efforts on studying the merits of individualization on non-serious games, especially based on physiological parameters. Notwithstanding, we see that the reported results could be transferred to serious contexts, but further investigation will be necessary to validate this.

7.3. Limitations of the SLR & Possible Future Work

Although we have reviewed a plethora of research works on individualization, our SLR is mainly focused on the aspects of the players facet used for driving the individualization. As such, reported results on the facets related to aspects of the game and the individualization rules/strategies are limited. The realization of any successful individualized experience requires a close coordination and implementation of all three facets. In light of this, a systematically review of the literature on the remaining two facets in order to better comprehend the state of the art on individualized serious games is also needed. Furthermore, and due to the nature of a SLR, it is possible that we missed interesting work that was either not indexed in the libraries considered or was not found using the used search string. Also, due to the fact that we limited our SLR to (serious) games, work on individualization in the context of other systems, such as intelligent tutoring systems or e-learning systems, and aspects of users used in those contexts, are also not covered.

Next, and as already indicated in the discussion, a standardized terminology for classifying different aspects in the context of individualization is lacking or at least not used in the works on individualization. Therefore, the same terms may have been used differently in different papers, and different terms may have been used for the same aspect in different papers. Compiling such a standardized terminology could also be an interesting research work. Furthermore, the numbers for some results are small, and therefore using them for comparison and trend detection purposes may not be well founded.

Player Aspect	Measurement Method	Effect Intended for	Targeted Game Aspect(s)	Methodology	Results	Limitations	Game Type - Application Area	Year	Source(s)
Performance - task skill	Webcam to track movements	Playability; Usability	DDA (Speed and difficulty of the game)	Two phases: 10 able-bodies participants for formative evaluation; next evaluation with 3 disabled participants	Perceived positively, but speeding up DDA was too fast	Small sample size (3 disabled participants); no control condition	ExerGame - Physical rehabilitation (stroke)	2009	[42]
Performance - task skill	In-game performance	Training outcome	DDA	Within-group study with 7 post stroke participants - 3 conditions (no Difficulty Adaptation (DA), Incremented DA, Dynamic DA)	Significantly higher training outcome with DDA	Small sample size (7 disabled participants)	ExerGame - Physical rehabilitation (stroke)	2015	[13]
Performance - task skill	In-game performance	Game experience	DDA (speed , accuracy, range of motion)	Evaluation with 3 patients over 3 weeks	Positive for game experience	Small sample size (3 patients); no control condition	ExerGame - Physical rehabilitation (Parkinson disease)	2013	[43]
Performance - task skill	Measuring hand velocity by hardware device (Bimeo arm rehabilitation system)	Motivation; exercise intensity	DDA	Two phases: within-group study with 32 pairs of unimpaired participants - 3 conditions: no, manual and automatic adaptation; next within-group study with 5 pairs (1 impaired and 1 unimpaired) - 2 conditions (manual and automatic adaptation)	Both manual and automatic DA resulted to higher motivation and exercise intensity	Small sample size with target audience (3 pairs); no control condition for second evaluation (impaired/unimpaired pairs)	ExerGame - Physical rehabilitation (arm)	2017	[44]
Performance - task skill	In-game performance	Learning outcome; engagement	DDA	Between-group study with 28 participants - 2 conditions (adaptive and no adaptation)	Higher learning gains for the adaptive version, but no difference in engagement		Serious game (medical Triage training)	2014	[47]
Performance - task skill	in-game performance (average of response time, number of wrong answers, number of redundant faults)	learning outcome	DDA	Between-group study with 230 players - 3 conditions (no adaptation, adaptive and exp. adaptative)	Higher learning effect for adapted version	Little details about participants and no info on statistical significancy	Serious game (basic math)	2017	[48]
Performance - attention score	In-game performance	Game experience	DDA	Pilot study with 11 participants	Positive for game experience	Small sample size (11 participants); no control condition; pilot study	Serious game (attention training)	2019	[49]

Performance - player experience and behavior	In-game performance	Cooperation competency	DDA; content generation	Pilot study with 6 adult participants	Average level of cooperation increased but cause not clear	Small sample size (6 participants); participants were not part of target audience; no control condition; pilot study	Serious game (conflict resolution)	2011	[54]
Performance - knowledge and learning progress	In-game performance; player behavior	Learning outcome	Feedback and interventions (hints)	Between-groups study with 40 participants – 2 conditions (adaptive feedback and no adaptive feedback)	Faster problem-solving process with adaptive feedback		Serious game (optics physics)	2008	[59]
Performance - preference and behavior	On-screen questions at the start of the game; in-game behavior and performance	Learning outcome; game experience	Story pace and construction; feedback and hints	Evaluation with 16 boys (paired up)	Promising but no control group to compare with	Small sample size (8 pairs); only boys, no control condition	Serious game (geography)	2012	[60]
Performance	In-game performance; player behavior	Learning outcome; game experience	Adaptive dialogue difficulty; performance feedback; motivational support; meta-cognitive hints	Between-groups study with 83 participants – 2 conditions (basic adaptive and advanced adaptive)	Better learning outcome for advanced adaptation(not statistically significant); perceived better (statistically significant); better immersion (not statistically significant)		Serious game (language learning)	2010	[15]
Performance	Assessment of user knowledge through Dynamic Bayesian networks	Learning outcome	Feedback	Between-groups study with 44 participants – 3 conditions (no adaptation, pedagogical agent and old student model, pedagogical agent and new student model)	No differences		Serious game (math)	2009	[62]
Performance	In-game performance	Game preference; performance	DDA	Within-subject deisgn with 8 participants	The ones that played the adapted version first performed worse than the one that played the original version first	Very small sample size; participants were friends and family of the developers	Serious game (lifestyle guidance for teenagers)	2018	[12]
Performance	Monitoring the user movements with 3D motion capture sensor (Kinect Xbox One) and a virtual reality head-mounted device	Training outcome	DDA; instructions	Pilot study with 5 patients and 3 therapists	Participants appreciated the proposed solution	Small sample size (5 patients, 3 therapist); no control condition; pilot study	ExerGame - Physical rehabilitation	2019	[45]

Performance - task skill	User skills; in-game performance	Training outcome (required skills); user motivation	DDA	Theoretical evaluation of recommender system, usability with between-groups study with 6 participants - 2 conditions (game and paper-based exercises)	Satisfactory and better than for the traditional exercises	Small sample size (6 participants); pilot study; user motivation only through simulation	ExerGame - Physical rehabilitation	2019	[46]
Performance	Kinect-based recognition of pose and activity	Learning outcome	Training paths	Between-groups study with 10 participants – 2 conditions (kinect-based and video-based)	Better learning performance than traditional video-based method	Small sample size (10 participants)	ExerGame	2019	[57]
Knowledge level	Quizzes	Learning outcome	DDA	Study with 60 participants	Very positive and encouraging	Questionnaire to measure effect; no control group; participants were students in a course on HTML	Serious game (computer science - HTML)	2019	[58]
Performance	In-game performance; player behavior	Learning outcome	Rewards	In-lab multi-agent simulator	Substantial performance gains (in behavior change metrics, speed and success rates) compared to a static reward scheme	No true empirical evaluation with actual participants, but using a simulation	Serious game (behavior change)	2019	[63]

Table 1: Summary of the literature review on using performance as the aspect of the player for individualization

Player Aspect	Measurement Method	Effect Intended for	Targeted Game Aspect(s)	Methodology	Results	Limitations	Game Type - Application Area	Year	Source(s)
Anxiety level	Physiological signals measured through sensors using regression tree to derive the anxiety level	Performance; game experience	DDA	Within-group study with 9 participants - 2 conditions (affect-based DDA, performance-based DDA)	Improved performance and more challenge for affect-based DDA	Small sample size (9 participants); not in context of serious game	Entertain-ment game (pong)	2009	[64]
Stress level	Measuring facial physiology by means of a thermal imaging-based stress monitoring and analysis system, known as StressCam	game experience	DDA	Within-group study with 14 participants - 3 conditions (easy, difficult, auto-difficulty)	Better game experience for auto-difficulty	Relatively small sample size (14 participants); not in context of serious game	Entertain-ment game (shooting)	2009	[65]
Static information (such as training plans) + vital parameters (speed, revolution per minute, watt and heartrate)	Player behavior and the vital status are measured via sensor technology and compared to the authored training plans	User motivation	DDA	Technical feasibility studies and focus group tests with 26 participants in total	Higher motivation	Limited info; no control group	ExerGame (sport, fitness)	2010	[35]
Heart rate, speed, cadence	Ergometer	User motivation	Controlling the game	Study with 48 participants with 3 games	Motivating, effect was depending on gender and self-reported fitness	No control condition; only one game used heart rate	ExerGame (indoor cardiac training)	2012	[66]
Breathing rate	Respiratory sensor	Learning outcome	DDA	Between-group study with 9 participants - 3 conditions (biofeedback game, original game, no game but deep breathing)	Biofeedback more effective in short term learning transfer and significant lower arousal	Small sample size (9 participants); only short term learning effect measured	Serious game (relaxation)	2013	[67]
Affective and physiological states	GSR (Galvanic Skin Response) to measure skin resistance, plethysmograph to measure relative blood pleasure, respiration belt to estimate abdomen extension, a temperature sensor to measure palmar temperature changes, and self-reported data	Game experience	DDA	Within-group study with 20 participants - 3 conditions (easy, medium, difficult)	Different difficulty resulted in different emotional states (two with reasonable accuracy); engagement could decrease if difficulty did not change according to the skills	Not in the context of serious games	2D entertainment game (Tetris)	2009	[71]

Affective and physiological states	GSR (Galvanic Skin Response) to measure skin resistance, plethysmograph to measure relative blood pleasure, respiration belt to estimate abdomen extension, a temperature sensor to measure palmar temperature changes, EEG, and self-reported data	Game experience	DDA	Within-group study with 20 participants - 3 conditions (easy, medium, difficult) (same as [71])	Using EEG for short-term emotion is more robust	Not in the context of serious games	2D entertainment game (Tetris)	2011	[72]
Attention based on eye tracking	Tobii eye tracker	Learning outcome; game performance	Adaptive hints	Study with 12 participants	Eye movement patterns affected by existing user knowledge, hint timing, and attitude toward getting help; no improvement for performance; attention to hints decreased during gameplay; further investigation needed for adaptive hints	Relatively small sample size (12 participants); no control condition	Serious game (number factorization)	2012	[73]
Player's mental state (anxiety, boredom, flow) - in-game performance and self-reported state of flow	Heart-rate and beta band of their brain wave; game logs	Game experience; in-game performance	DDA; environmental settings to increase the flow experience of players	Within-group study with 21 participants - 2 conditions (state-based adapted, performance-based adapted)	Negative: Higher levels of flow and significantly higher in-game scores for the performance-based adaptation	Methods used for training the classifier for the mental-based version seemed to be unreliable; not in the context of serious game	Non-serious game (FPS)	2018	[74]

Table 2: Summary of the literature review on using physiological parameters and affective states as the aspect of the player for individualization

Player Aspect	Measurement Method	Effect Intended for	Targeted Game Aspect(s)	Methodology	Results	Limitations	Game Type/Application Area	Year	Source(s)
Learning style	Self-report questionnaire The Index of Learning Styles (ILS)	Learning motivation; learning outcome; perceived ease of use; perceived usefulness	Interface; content presentation	Between-group study with 46 participants - 2 conditions (learning style-based adapted, no adaptation)	Significant better learning outcome and motivation, higher perceived usefulness and perceived ease of use for adapted version		Serious game (natural science)	2012	[9]
Learning style, playing style	Self-report questionnaires	Retention and engagement	Learning content adjustment	Between-group study with 64 participants - 2 conditions (game, classical teaching method)	Tentative promise for game in being more engaging; no significant differences in retention	No comparison with non-adapted game	Serious game (computer programming)	2018	[10]
Multiple Intelligences profile	Self-report questionnaires (MIPQ)	Game experience	Game mechanics targeting specific dimension of MI based on an evidence-based mapping	Between-group study with 22 participants - 2 conditions (bodily kinesthetic intelligence, other dominant intelligence; same game)	Higher level of competence and immersion, and lower tension and negative affect for bodily kinesthetic users	Relatively small sample size (11 per condition); not in the context of serious game	Non-serious game (Leapmotion based)	2016	[78]
Multiple Intelligences profile	Self-report questionnaires (MIPQ)	Game experience; learning outcome	Game mechanics targeting specific dimension of MI based on an evidence-based mapping	Pilot study with 4 participants for measuring learning outcome and 11 for game experience; between-group method	Higher level of immersion, flow and competence, and improved learning outcome for logically-mathematically intelligent players	Very small sample size (4 and 11 participants)	Serious game (proposition logic)	2016, 2018	[79, 82]
Personality	Self-reported questionnaire (MBTI personality test)	Learning outcome; engagement	Game mechanics	Between-group study with 29 participants - 2 conditions (adaptive, non-adaptive)	Significant difference between the adapted and the non-adapted version for engagement; no significant difference for learning outcome	Relatively small sample size (15/14 participants per condition)	Serious game (language learning)	2016	[83]
Personality	Self-reported questionnaire (Big Five Inventory Questionnaire)	Motivation; cognitive load; technology acceptance (ease of use, usefulness, intention to use)	Learning content adjustment; game mechanics adjustment	Between-group study with 51 participants - 2 conditions (adaptive, non-adaptive)	Significantly decrease of cognitive load, and significant higher degree of perceived usefulness and intention for adaptive version; no differences in motivation		Serious game (computer science - networking and internet concepts)	2019	[86]

Cognitive style	self-reported questionnaire (SPQ)	Learning outcome; game perception	Game mechanics	Two between-group studies, each with 60 participants, both with 2 conditions (player-customization vs no-customization, and pre-customized vs no-customization)	More positive perception with player-customization; more negative perception with pre-customization; both useful for enhancing learning performance; holist player may not favor to listen to music, serialist may not prefer hints	Two different studies to compare player customized with automatic personalization (no control conditions for each study)	Serious game (reasoning, logical mathematical and strategic thinking)	2016	[88]
Personal data - images/videos from daily life	Camera around the neck that captured images every 30 seconds, used 7 hours a day for one month	User adherence; enjoyment; cognitive intervention	Game content (images and videos for the puzzles)	With-in group study with 26 participants over 3 months - 2 conditions (personalized, non-personalized)	Higher adherence to play and higher enjoyment the personalized version. No differences for overall preference, content preference, game mechanism preference, and cognitive functioning	Different games used for personalized and non-personalized conditions. Discrepancies between results may suggesting other influencing factors	Serious game (memory, attention, speed, visuo-spatial, and executive functioning)	2018	[89]
Learning style	Two methods: questionnaire (Felder-Silverman) and user interaction	Learning outcome	Learning content adjustment	Between-groups study with 120 participants - 4 conditions (textbook, game no adaptivity game, adaptative game based on questionnaire, in-game adaptive game based on student's interaction)	All game versions resulted in significant better learning outcomes than textbook; the adaptive versions resulted in the highest learning effectiveness; but no difference between the two adaptative versions		Serious game (computer science - SQL)	2015	[76]

Table 3: Summary of the literature review on using personal traits of the player for individualization

8. Conclusions

The article started by arguing for why taking individual differences among players into account is important for the success of a serious game. Next, we provided a comprehensive overview of the different forms of individualization in the literature, as well as the different facets it involves. Subsequently, we reported on the systematic literature review performed, focusing on the aspects of the players that can be used for the individualization of serious games. Next we presented the findings, followed by a discussion about their implications. An overview of our findings was given by means of three tables that summarize the player aspects considered, the instruments/methods used for measuring these aspects, the intended effects, and the game aspects targeted for the individualization, as well as a summary of the (empirical) evaluation performed, and the context of this evaluation, i.e., the application domain or topic of the employed game.

We analysed the findings from different points of view, including the distribution of the player aspects encountered, distribution of the game aspects individualized, distribution of the studied effects, and of the context of the works, as well as an overview of the evolution of the focus of the works over the years. The overarching goal of this paper was to investigate the question *"which aspects of players for individualization are most frequently researched?"*. Our review has revealed that players' performance such as in-game performance and task skill are among the most widely researched player aspects in individualization. This was followed by physiological parameters & affective states, and personal traits as other player aspects that are studied in the literature, but not to the same extent. Performance is definitely the most straight forward aspect of players that can be measured in a game based on objective indicators such as number of errors, success rate, points, etc. However, measuring aspects related to physiological parameters & affective states are highly intrusive and expensive to perform even in experimental settings, and aspects such as personality traits are mostly based on subjective self-reported measures from players which makes their reliability questionable. As such, most of the effort and attention in the literature has gone to performance. As the technology evolves however, and less intrusive and more reliable methods for measuring these aspects of players emerge, we expect to witness a growth in the use of these user aspects for individualization purposes.

Perhaps the most important trend that our SLR has unveiled is the lack of rigorous evaluations in the literature on the effectiveness of individualization. A significant number of the reviewed works in this paper performed an evaluation with a very small sample size, and in some cases without a methodical comparison against a proper control condition. These limitations highlight the necessity for more evaluations, with larger populations, and using robust methods for evaluating the effectiveness of individualization. Furthermore, with the exception of one work, none of the reviewed researches have investigated the longitudinal effect of individualization on the experience and learning of players. The lack of longitudinal studies has been a pertinent issue in the technology-enhanced education domain, and while in recent years we are witnessing efforts to mitigate this situation, our understanding of the implication of technology on education and concepts such as individualization are still in infancy.

This systematic literature review is useful for researchers in the serious game community, as it shows which player aspects are already well investigated for individualization and which are not yet. We also indicated areas for future research in this context. Furthermore, it can help researchers and practitioners in making informed decisions regarding what aspects of players to use for achieving a successful individualization in a particular serious game.

References

[1] U. Ritterfeld, M. Cody, P. Vorderer, Serious games: Mechanisms and effects, Routledge, 2009.

[2] R. Dörner, S. Göbel, W. Effelsberg, J. Wiemeyer, Introduction, in: Serious Games., Springer, 2016. `doi:https://doi.org/10.1007/978-3-319-40612-1_1`.

[3] D. Charles, M. Mcneill, M. McAlister, M. Black, A. Moore, K. Stringer, J. Kücklich, A. Kerr, Player-centred game design: Player modelling and adaptive digital games (2005) 285–298`doi:10.1.1.97.735`.

[4] R. Lopes, R. Bidarra, Adaptivity challenges in games and simulations: a survey, IEEE Transactions on Computational Intelligence and AI in Games 3 (2) (2011) 85–99.

[5] M. D. Kickmeier-Rust, D. Albert, Micro-adaptivity: Protecting immersion in didactically adaptive digital educational games, Journal of Computer Assisted Learning 26 (2) (2010) 95–105.

[6] R. A. Sottilare, S. Gilbert, Considerations for adaptive tutoring within serious games: authoring cognitive models and game interfaces, Tech. rep., ARMY RESEARCH LAB ORLANDO FL HUMAN RESEARCH AND ENGINEERING DIRECTORATE (2011).

[7] M. Vandewaetere, F. Cornillie, G. Clarebout, P. Desmet, Adaptivity in educational games: Including player and gameplay characteristics., International Journal of Higher Education 2 (2) (2013) 106–114.

[8] P. Sajjadi, F. Van Broeckhoven, O. De Troyer, Dynamically adaptive educational games: A new perspective, in: International Conference on Serious Games, Springer, 2014, pp. 71–76.

[9] G.-J. Hwang, H.-Y. Sung, C.-M. Hung, I. Huang, C.-C. Tsai, Development of a personalized educational computer game based on students learning styles, Educational Technology Research and Development 60 (4) (2012) 623–638.

[10] R. S. Lindberg, T. H. Laine, Formative evaluation of an adaptive game for engaging learners of programming concepts in k-12, International Journal of Serious Games 5 (2) (2018) 3–24.

[11] B. Magerko, C. Heeter, J. Fitzgerald, B. Medler, Intelligent adaptation of digital game-based learning, in: Proceedings of the 2008 Conference on Future Play: Research, Play, Share, 2008, pp. 200–203.

[12] M. Hendrix, T. Bellamy-Wood, S. McKay, V. Bloom, I. Dunwell, Implementing adaptive game difficulty balancing in serious games, IEEE Transactions on Games.

[13] N. Hocine, A. Gouaich, S. A. Cerri, Dynamic difficulty adaptation in serious games for motor rehabilitation, in: International Conference on Serious Games, Springer, 2014, pp. 115–128.

[14] S. Oberdörfer, M. E. Latoschik, Develop your strengths by gaming: Towards an inventory of gamificationable skills, INFORMATIK 2013–Informatik angepasst an Mensch, Organisation und Umwelt.

[15] N. Peirce, V. Wade, Personalised learning for casual games: The'language trap'online language learning game, Leading Issues in Games Based Learning 159.

[16] O. De Troyer, Towards effective serious games, in: 2017 9th International Conference on Virtual Worlds and Games for Serious Applications (VS-Games), IEEE, 2017, pp. 284–289.

[17] R. Bartle, Hearts, clubs, diamonds, spades: Players who suit muds, Journal of MUD research 1 (1) (1996) 19.

[18] J. Hamari, J. Tuunanen, Player types: A meta-synthesis.

[19] M. Csikszentmihalyi, I. S. Csikszentmihalyi, Optimal experience: Psychological studies of flow in consciousness, Cambridge university press, 1992.

[20] D. J. Shernoff, M. Csikszentmihalyi, B. Schneider, E. S. Shernoff, Student engagement in high school classrooms from the perspective of flow theory, in: Applications of flow in human development and education, Springer, 2014, pp. 475–494.

[21] P. Sweetser, P. Wyeth, Gameflow: a model for evaluating player enjoyment in games, Computers in Entertainment (CIE) 3 (3) (2005) 3–3.

[22] B. Cowley, D. Charles, M. Black, R. Hickey, Toward an understanding of flow in video games, Computers in Entertainment (CIE) 6 (2) (2008) 1–27.

[23] J. Webster, L. K. Trevino, L. Ryan, The dimensionality and correlates of flow in human-computer interactions, Computers in human behavior 9 (4) (1993) 411–426.

[24] K. Kiili, Digital game-based learning: Towards an experiential gaming model, The Internet and higher education 8 (1) (2005) 13–24.

[25] J. H. Murray, J. H. Murray, Hamlet on the holodeck: The future of narrative in cyberspace, MIT press, 2017.

[26] C. Dede, Immersive interfaces for engagement and learning, science 323 (5910) (2009) 66–69.

[27] B. Kitchenham, S. Charters, Guidelines for performing systematic literature reviews in software engineering (2007).

[28] S. Bakkes, C. T. Tan, Y. Pisan, Personalised gaming: a motivation and overview of literature, in: Proceedings of the 8th Australasian Conference on Interactive Entertainment: Playing the System, 2012, pp. 1–10.

[29] S. Karpinskyj, F. Zambetta, L. Cavedon, Video game personalisation techniques: A comprehensive survey, Entertainment Computing 5 (4) (2014) 211–218.

[30] A. Streicher, J. D. Smeddinck, Personalized and adaptive serious games, in: Entertainment Computing and Serious Games, Springer, 2016, pp. 332–377.

[31] J. L. Pituba, R. Nakamura, Assessing the strategies of adaptation of adaptive educational games, in: Conferência de Ciências e Artes dos Videojogos–VIDEOJOGOS, 2014.

[32] B. Beldagli, T. Adiguzel, Illustrating an ideal adaptive e-learning: A conceptual framework, Procedia-Social and Behavioral Sciences 2 (2) (2010) 5755–5761.

[33] C. Glahn, Adaptation And Personalization, Tech. rep. (2010).
URL http://www.slideshare.net/phish108/adaptation-and-personalization

[34] J. Linssen, Adaptive learning in an educational game–adapting game complexity to gameplay increases efficiency of learning, Master's thesis (2011).

[35] S. Göbel, S. Hardy, V. Wendel, F. Mehm, R. Steinmetz, Serious games for health: personalized exergames, in: Proceedings of the 18th ACM international conference on Multimedia, 2010, pp. 1663–1666.

[36] P. Sajjadi, Individualizing learning games: Incorporating the theory of multiple intelligences in player-centered game design, Vrije Universiteit Brussel.

[37] D. Charles, M. Black, Dynamic player modeling: A framework for player-centered digital games, in: Proc. of the International Conference on Computer Games: Artificial Intelligence, Design and Education, 2004, pp. 29–35.

[38] H. Gardner, The theory of multiple intelligences, Heinemann, 1983.

[39] C. Karagiannidis, D. Sampson, Adaptation rules relating learning styles research and learning objects meta-data, in: Workshop on Individual Differences in Adaptive Hypermedia. 3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems (AH2004), Eindhoven, Netherlands, Citeseer, 2004.

[40] P. Brusilovsky, Methods and techniques of adaptive hypermedia, in: Adaptive hypertext and hypermedia, Springer, 1998, pp. 1–43.

[41] D. Hauger, M. Köck, State of the art of adaptivity in e-learning platforms., in: LWA, 2007, pp. 355–360.

[42] J. W. Burke, M. McNeill, D. K. Charles, P. J. Morrow, J. H. Crosbie, S. M. McDonough, Optimising engagement for stroke rehabilitation using serious games, The Visual Computer 25 (12) (2009) 1085.

[43] J. D. Smeddinck, S. Siegel, M. Herrlich, Adaptive difficulty in exergames for parkinson's disease patients., in: Graphics Interface, 2013, pp. 141–148.

[44] M. Goršič, A. Darzi, D. Novak, Comparison of two difficulty adaptation strategies for competitive arm rehabilitation exercises, in: 2017 international conference on rehabilitation robotics (ICORR), IEEE, 2017, pp. 640–645.

[45] I. Afyouni, A. Einea, A. Murad, Rehabot: Gamified virtual assistants towards adaptive telerehabilitation, in: Adjunct Publication of the 27th Conference on User Modeling, Adaptation and Personalization, 2019, pp. 21–26.

[46] C. S. González-González, P. A. Toledo-Delgado, V. Muñoz-Cruz, P. V. Torres-Carrion, Serious games for rehabilitation: Gestural interaction in personalized gamified exercises through a recommender system, Journal of biomedical informatics 97 (2019) 103266.

[47] H. van Oostendorp, E. D. Van der Spek, J. Linssen, Adapting the complexity level of a serious game to the proficiency of players., EAI Endorsed Trans. Serious Games 1 (2) (2014) e5.

[48] A. Belahbib, L. Elaachak, M. Bouhorma, O. B. Yedri, S. Abdelali, E. Fatiha, Serious games adaptation according to the learner's performances, International Journal of Electrical and Computer Engineering 7 (1) (2017) 451.

[49] N. Hocine, M. Ameur, W. Ziani, Keep attention: A personalized serious game for attention training., in: GamiLearn, 2019.

[50] M. D. Kickmeier-Rust, N. Peirce, O. Conlan, D. Schwarz, D. Verpoorten, D. Albert, Immersive digital games: the interfaces for next-generation e-learning?, in: International Conference on Universal Access in Human-Computer Interaction, Springer, 2007, pp. 647–656.

[51] M. D. Kickmeier-Rust, S. Göbel, D. Albert, 80days: Melding adaptive educational technology and adaptive and interactive storytelling in digital educational games, in: Proceedings of the First International Workshop on Story-Telling and Educational Games (STEG'08), Vol. 8, 2008.

[52] S. Göbel, F. Mehm, S. Radke, R. Steinmetz, 80days: Adaptive digital storytelling for digital educational games, in: Proceedings of the 2nd international workshop on Story-Telling and Educational Games (STEG'09), Vol. 498, 2009.

[53] G. N. Yannakakis, J. Togelius, R. Khaled, A. Jhala, K. Karpouzis, A. Paiva, A. Vasalou, Siren: Towards adaptive serious games for teaching conflict resolution, Proceedings of ECGBL (2010) 412–417.

[54] C. Grappiolo, Y.-G. Cheong, J. Togelius, R. Khaled, G. N. Yannakakis, Towards player adaptivity in a serious game for conflict resolution, in: 2011 Third International Conference on Games and Virtual Worlds for Serious Applications, IEEE, 2011, pp. 192–198.

[55] Y.-g. Cheong, C. Holmg, F. Berger, Towards Validating Game Scenarios for Teaching Conflict Resolution, in: Games for learning workshop at FDG (Foundations of Digital Games), Chania, Crete, Citeseer, 2013, pp. 2–5.

[56] K. Karpouzis, G. Yannakakis, A. Paiva, J. H. Nielsen, A. Vasalou, A. Jhala, User modelling and adaptive, natural interaction for conflict resolution, Proceedings - 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, ACII 2013 (2013) 719–721doi:10.1109/ACII.2013.131.

[57] M. Xu, Y. Zhai, Y. Guo, P. Lv, Y. Li, M. Wang, B. Zhou, Personalized training through kinect-based games for physical education, Journal of Visual Communication and Image Representation 62 (2019) 394–401.

[58] S. Papadimitriou, K. Chrysafiadi, M. Virvou, Fuzzeg: Fuzzy logic for adaptive scenarios in an educational adventure game, Multimedia Tools and Applications 78 (22) (2019) 32023–32053.

[59] M. D. Kickmeier-Rust, B. Marte, S. Linek, T. Lalonde, D. Albert, The effects of individualized feedback in digital educational games, in: Proceedings of the 2nd European Conference on Games Based Learning, Academic Publishing Limited, 2008, pp. 227–236.

[60] E. L.-C. Law, X. Sun, Evaluating user experience of adaptive digital educational games with activity theory, International Journal of Human-Computer Studies 70 (7) (2012) 478–497.

[61] N. Peirce, O. Conlan, V. Wade, Adaptive educational games: Providing non-invasive personalised learning experiences, in: 2008 second IEEE international conference on digital game and intelligent toy enhanced learning, IEEE, 2008, pp. 28–35.

[62] C. Conati, M. Manske, Adaptive feedback in an educational game for number factorization, in: Proceedings of the 2009 conference on Artificial Intelligence in Education: Building Learning Systems that Care: From Knowledge Representation to Affective Modelling, IOS Press, 2009, pp. 581–583.

[63] Y. Semet, B. Marcon, K. Demestichas, N. Koutsouris, A. Ascolese, Artificial ant colonies for adaptive rewards in serious games, in: Artificial Life Conference Proceedings, MIT Press, 2019, pp. 533–540.

[64] C. Liu, P. Agrawal, N. Sarkar, S. Chen, Dynamic difficulty adjustment in computer games through real-time anxiety-based affective feedback, International Journal of Human-Computer Interaction 25 (6) (2009) 506–529.

[65] C. Yun, D. Shastri, I. Pavlidis, Z. Deng, O'game, can you feel my frustration? improving user's gaming experience via stresscam, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2009, pp. 2195–2204.

[66] S. Hardy, S. Göbel, M. Gutjahr, J. Wiemeyer, R. Steinmetz, Adaptation model for indoor exergames, Int J Comput Sci Sport 11 (1) (2012) 73–85.

[67] A. Parnandi, B. Ahmed, E. Shipp, R. Gutierrez-Osuna, Chill-out: Relaxation training through respiratory biofeedback in a mobile casual game, in: International Conference on Mobile Computing, Applications, and Services, Springer, 2013, pp. 252–260.

[68] S. Asteriadis, P. Tzouveli, K. Karpouzis, S. Kollias, Estimation of behavioral user state based on eye gaze and head pose-application in an e-learning environment, Multimedia Tools and Applications 41 (3) (2009) 469–493.

[69] S. Asteriadis, N. Shaker, K. Karpouzis, G. N. Yannakakis, Towards player's affective and behavioral visual cues as drives to game adaptation, LREC, 2012.

[70] G. N. Yannakakis, J. Togelius, Experience-driven procedural content generation, in: 2015 International Conference on Affective Computing and Intelligent Interaction (ACII), IEEE, 2015, pp. 519–525.

[71] G. Chanel, C. Rebetez, M. Bétrancourt, T. Pun, Boredom, engagement and anxiety as indicators for adaptation to difficulty in games, in: Proceedings of the 12th international conference on Entertainment and media in the ubiquitous era, 2008, pp. 13–17.

[72] G. Chanel, C. Rebetez, M. Bétrancourt, T. Pun, Emotion assessment from physiological signals for adaptation of game difficulty, IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 41 (6) (2011) 1052–1063.

[73] M. Muir, C. Conati, An analysis of attention to student–adaptive hints in an educational game, in: International Conference on Intelligent Tutoring Systems, Springer, 2012, pp. 112–122.

[74] T. Alves, S. Gama, F. S. Melo, Flow adaptation in serious games for health, in: 2018 IEEE 6th International Conference on Serious Games and Applications for Health (SeGAH), IEEE, 2018, pp. 1–8.

[75] R. M. Felder, L. K. Silverman, et al., Learning and teaching styles in engineering education, Engineering education 78 (7) (1988) 674–681.

[76] M. Soflano, T. M. Connolly, T. Hainey, An application of adaptive games-based learning based on learning style to teach sql, Computers & Education 86 (2015) 192–211.

[77] P. Honey, A. Mumford, Learning styles questionnaire, Organization Design and Development, Incorporated, 1989.

[78] P. Sajjadi, A. Lo-A-Njoe, J. Vlieghe, O. De Troyer, Exploring the relation between game experience and game mechanics for bodily-kinesthetic players, in: International Conference on Games and Learning Alliance, Springer, 2016, pp. 354–364.

[79] P. Sajjadi, E. El Sayed, O. De Troyer, On the impact of the dominant intelligences of players on learning outcome and game experience in educational games: The truebiters case, in: International Conference on Games and Learning Alliance, Springer, 2016, pp. 221–231.

[80] P. Sajjadi, J. Vlieghe, O. De Troyer, Relation between multiple intelligences and game preferences: an evidence-based approach, in: European Conference on Games Based Learning, Academic Conferences International Limited, 2016, p. 565.

[81] P. Sajjadi, J. Vlieghe, O. De Troyer, Evidence-based mapping between the theory of multiple intelligences and game mechanics for the purpose of player-centered serious game design, in: 2016 8th International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES), IEEE, 2016, pp. 1–8.

[82] O. De Troyer, R. Lindberg, J. Maushagen, P. Sajjadi, Development and evaluation of an educational game to practice the truth tables of logic, in: 2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT), Vol. 2161, IEEE, 2019, pp. 92–96.

[83] N. Shabihi, F. Taghiyareh, M. H. Abdoli, Analyzing the effect of game-elements in e-learning environments through mbti-based personalization, in: 2016 8th International Symposium on Telecommunications (IST), IEEE, 2016, pp. 612–618.

[84] M. T. Quinn, R. J. Lewis, K. L. Fischer, A cross-correlation of the myers-briggs and keirsey instruments., Journal of College Student Development.

[85] G. J. Boyle, Myers-briggs type indicator (mbti): some psychometric limitations, Australian Psychologist 30 (1) (1995) 71–74.

[86] A. Tlili, M. Denden, F. Essalmi, M. Jemni, N.-S. Chen, R. Huang, et al., Does providing a personalized educational game based on personality matter? a case study, IEEE Access 7 (2019) 119566–119575.

[87] O. P. John, S. Srivastava, et al., The big five trait taxonomy: History, measurement, and theoretical perspectives, Handbook of personality: Theory and research 2 (1999) (1999) 102–138.

[88] O. Ku, C.-C. Hou, S. Y. Chen, Incorporating customization and personalization into game-based learning: A cognitive style perspective, Computers in Human Behavior 65 (2016) 359–368.

[89] Q. Xu, V. Subbaraju, C. H. Cheong, A. Wang, K. Kang, M. Bashir, Y. Dong, L. Li, J.-H. Lim, Personalized serious games for cognitive intervention with lifelog visual analytics, in: Proceedings of the 26th ACM international conference on Multimedia, 2018, pp. 328–336.

[90] P. Sajjadi, L. Hoffmann, P. Cimiano, S. Kopp, A personality-based emotional model for embodied conversational agents: Effects on perceived social presence and game experience of users, Entertainment Computing 32 (2019) 100313.