Small Data as a tool to predict player game design preferences: a qualitative pilot study

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Abstract

Videogames, besides a form of entertainment, can be of added value to purposes such as physical rehabilitation (serious games). In this context, custom made serious games may be of great value, especially if they combine the necessary actions that the user must perform with engaging and captivating gameplay. Given data protection and ethical constraints, assessing a patient's gaming preferences and personal traits to predict preferred game design by big data from online social profiles is not possible. In this matter, we developed a questionnaire that tries to infer patients' gaming preferences from limited personal information, which we denote as "Small Data". The questionnaire was tested in a pilot study with 17 healthy participants and results suggest that the collected information may help decide what kind of videogame better suits a particular patient, potentially aiding the process of developing Serious Games for healthcare.

Keywords: serious games, game design, player type taxonomy, video games

1. Introduction

Videogames come in a vast panoply of genres, featuring several different types of gameplays and tackling a variety of ends that range from entertainment to serious purposes (usually known as serious games), such as aiding healthcare.

Past studies have shown that, when videogames are used as a complement for physical rehabilitation, there's a gap between significant clinical results and the players' enjoyment of the game in question [13]. Players seem to enjoy commercial videogames that were not designed with healthcare in mind more, while custom made games may be perceived as less enjoyable but typically attain better clinical results [6]. This creates a need for custom made games that patients enjoy as much as commercial titles. Therefore, a question was raised: is it possible to understand player preferences to posteriorly select a game genre and gameplay characteristics that are bound to motivate and immerse the player more?

Within this spectrum of player preferences as an indicator of possible game enjoyment, big data (large data sets that, when analyzed, may reveal patterns, trends and associations that are often related to both human behavior and interactions) is already used to know player preferences. Such is done in renowned gaming platforms like Steam or PSN. However, in clinical contexts where patient privacy is vital, such approach is not viable. This study investigated ways of using "small data" (the opposite of big data) to have access to personal user preferences to approach custom made games to what the players would ideally want. Small data implies the use of small data sets that are analyzed computationally to draw conclusions (in this specific case, in terms of player preferences). For this purpose, a new questionnaire using small data to predict player preferences was developed and its validity was tested among healthy participants.

2. Background and Related Work

Over the years, several authors developed models that classified players according to the way they approached videogames.

Bartle's Player Types model was one of the first gamer models to emerge, dating back to 1996). It remains the most prevalent player type taxonomy, and it defines four different types of gamers, achievers, explorers, socializers and killers, each referring to a particular way players approach videogames, and the kind of user-videogame interaction they prefer [2]. The central downside of Bartle's model is that it focuses solely on MMORPG[1] videogames, therefore focusing its analysis on the type of gameplay and user-videogame interaction offered by games of this genre. Additionally, Bartle's model is not empirically based. Another disadvantage is that the types presented by Bartle are mutually exclusive, which is not something that happens in the real world [12].

Another model that can be used to achieve this categorization of player types in function of their gameplay style and preferences is Yee's MMORPG user motivation. Yee's model can be considered a game design taxonomy and, just like it happened with Bartle's model, Yee's also tackles MMORPG players only. This model analyses the main motivations that make people want to play videogames of the MMORPG genre and categorizes users accordingly. This model results in five different motivations: achievement, relationship, immersion, escapism and manipulation [14]. Although limited, this model brought forward a way of quantifying the originally qualitative principles presented by Bartle [9].

The Hexad User Types is a player type taxonomy model that was specifically designed to target gamification preferences and it offers six possible categorizations for videogame players: achiever, free spirit, philanthropist, socializer, disruptor, and player. This model has previously been evaluated in several studies on the personalization of gamification, which contributed to the development of a correlation between user types and gamification preferences [8].

The BrainHex model presents seven types of gamers, therefore offering yet another player type taxonomy: Achiever, Conqueror, Daredevil, Mastermind, Seeker, Socializer and Survivor. BrainHex is a model that presents a few advantages, starting by the fact that it is empirically validated and that it is accessible online to the general public. BrainHex consists of a 28-question questionnaire that aims to evaluate the user's preferences when it comes to videogames and their respective play styles [10]. Additionally, and unlike other models, BrainHex acknowledges that gamer types are not mutually exclusive, attributing a primary gamer type and a subtype to each user, which consequently allows for several combination of each of the gamer types to come into existence. This aspect consequently provides a much closer look at how game design characteristics may or may not suit a certain individual [12].

Nevertheless, BrainHex also has its faults, starting by the fact that it targets people who are gamers themselves, therefore demanding the users are familiar with different types of gameplays and gaming vocabulary. This may be a problem if the games to be

[1] Massive Multiplayer Online Role-Playing Game. Can be described as referring to multiplayer instances that allow their players to explore the same world together at the same time while interacting with each other.

developed are not to be used on patients who already possess some degree of knowledge of videogames themselves.

The Big Five model, also known as the OCEAN model, presents five different dimensions that describe a person's behaviour: agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience [11]. This model can be used to predict user's gamification preferences and, consequently, it may be usable to predict gameplay preferences, considering that the concept of gamification consists in game elements being applied to real-world situations in order to make them more interesting. However, it is considered the least suitable out of all the models that can be used to categorize players and their preferences [4].

Despite the existence of several models that try to box players into categories according to their preferences, to the best of our knowledge, none of them has been applied to a serious context. To fill this gap, a new questionnaire focusing on the use of small data to predict player preferences was developed with basis on the previously mentioned pre-existent models.

3. Objectives

The study presented in this paper aims to develop a questionnaire that allows player preferences to be collected and analyzed, so that they can posteriorly be used to aid the development of serious games for physical rehabilitation to better suit each patient and their particularities. To gauge the viability of the questionnaire and of its algorithm, a pilot study took place, where the tool was validated among healthy participants. For this purpose, 15 popular titles of each videogame genre were selected and linked to each of the game characteristics surveyed in the questionnaire. Upon answering the questionnaire, the participants would be asked to play two games according to their responses: one that would ideally match their preferences, and one picked at random. Posteriorly, gaming experience of the two games was evaluated and results of the intervention were analyzed.

Thus, this paper aims to understand if this approach is viable and can be used in the context of healthcare, more specifically among disabled patients.

4. Methods

4.1. Development of the questionnaire and of its respective algorithm

In this study, we designed a questionnaire that brought closer characteristics of videogames of each genre and player preferences. First, we selected the principal game genres within the world of videogames. We followed a categorization usually utilized in platforms such as Steam or PSN, therefore being widely accepted within the gaming community. The selected genres were the following: Action, Adventure, Cards/Puzzle/Casual, Fighting, FPS (first-person shooter), MMORPG, MOBA (multiplayer online battle game), Platform, Racing, Rhythm/Music, RPG (role-playing game), Simulation, Sports, Strategy, Visual Novel [1]. Afterwards, we made a list of all of the possible characteristics of games of each genre, focusing on what could tell each game apart from the other: game perspective (1st person, 3rd person), game-play mode (single player, multiplayer), game length (short/repetitive, long), graphic style (2D, 2.5D, 3D, pixelated, cartoony, photorealistic, top-down, flat sideview, anime, low poly, cel-shaded, retro 8-bit), level of player involvement required (time needed to complete the game/an instance of the game). Following this, and embodying some of the questions that could be found in the questionnaires of player models like BrainHex, a surveyable questionnaire was created.

The questionnaire that was created was split into three parts: a first part that consisted of questions to demographically characterize the participants; a second part made of multiple choice questions that focused on elements including game-play mode, player-perspective, graphic style and level of required involvement from the player's part; and a third part that featured questions whose answers were to be given through a Likert Scale (ranging from 0, "Strongly disagree", to 4, "Strongly agree") [7]. This third part focused on more specific aspects of the broader characteristics of videogames. These allow games, even from the same genre, to be told apart from each other and have the objective of better approaching actual player preferences. In total, the questionnaire[2] is composed by 40 questions (14 for the first two parts, and 26 for the Likert Scale section).

Following this step, we selected a popular game within the videogame community for each of the designated videogame genres. For this study, we opted for videogames that are widely popular in their own genre, with excellent ratings among the gaming community and that were accessible to be used in the study. Table 1 summarizes the titles selected for each genre.

Table 1. List of the selected games for each of the game genres.

Selected games for each genre	
Action	*God of War* (2018)
Adventure	*The Legend of Zelda: Breath of the Wild* (2017)
Cards/Puzzle/Casual	*Candy Crush* (2012)
Fighting	*Mortal Kombat 11* (2019)
FPS	*Call of Duty: Black OPS III* (2015)
MMORPG	*Final Fantasy XIV* (2010)
MOBA	*League of Legends* (2009)
Platform	*New Super Mario Bros. U Deluxe* (2019)
Racing	*Project Cars* (2015)
Rhythm/Music	*Osu!* (2007)
RPG	*Final Fantasy VII Remake* (2020)
Simulation	*Stardew Valley* (2016)
Sports	*eFootball PES 2020* (2019)
Strategy	*Battle for Wesnoth* (2003)
Visual Novel	*Steins;Gate* (2009)

To fulfil the objective of linking playable videogames to player preferences, the original questionnaire was then converted to make the questions target to the games instead of player preferences. With this objective, 15 instances of parts 2 and 3 of the questionnaire were created[3], each of them corresponding to each of the 15 games. To match the videogames to their respective characteristics, this characteristic-attribution questionnaire was sent out to gamers across the globe, asking them to classify each game accordingly. This allowed the creation of a features map for each videogame. 31 gamers answered the questionnaire anonymously. Moreover, this questionnaire is objective, and discrepancies between participants' answers were not expected.

Finally, an algorithm was developed[4], where user responses would be compared to each game's features map and would output which game was closer in characteristics to the user's personal preferences. Additionally, weights were given to the questions. During the development and testing of the algorithm, the weights and their scale were adjusted according to inputs and outputs of two experienced gamers.

4.2. Participants

Seventeen (17) participants (8 males and 9 females) completed the questionnaire and participated in the pilot study. Respondents' age ranged from 18 to 38 years, with an average of 24.1 years. This research has been conducted following the ethical requirements established by Universidade Católica Portuguesa board of ethics. All participants agreed to participate in their study and filled an informed consent document upon the start of the intervention.

4.3. Procedure

To test the validity of this questionnaire and its ability to predict what kind of videogame a certain individual would enjoy playing, a pilot study was conducted at the School of Arts of the Catholic University of Portugal on the 16th and 17th of September 2022. The

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[2] https://forms.gle/wTLQ4QmKVYcuxKLm8
[3] a template of the questionnaire was made available here https://forms.gle/5kZS6TMDVyKNsoZd9
[4] https://github.com/catmv/gamingpreferences

event was advertised among students, Professors and visitors of a parallel event by posters and word of mouth. This step had the objective of validating the relevance of the developed tool among healthy participants to gauge its future viability of being used among physically disabled but cognitively capable participants in need of physical rehabilitation.

All of the 15 games previously selected were made available on various platforms, such as iMac, PlayStation 4, iPad mini and a Nintendo Switch Lite. Each participant received a numerical code that would be used to identify them, allowing the algorithm to predict which game would better suit each participant. Additionally, the use of this numerical code allows a link to be established between the Questionnaire and both Game Experience Questionnaire (GEQ) instances. After answering the questionnaire, the algorithm would tell the participant which two games they were supposed to play: one that matched their personality and one picked at random. The participant would then have 15 minutes to play each of the games (totaling 30 minutes). Players were free to start by whichever of the two games they pleased. After the first 15 minutes had passed, the participant would then be invited to switch to the second videogame and would play it for another 15 minutes. There was no waiting time in-between games. Each participant started the game from its starting point. Afterwards, participants were invited to answer two instances (one referring to the videogame that matched their personality and one referring to the game that was randomly picked by the algorithm, respectively) of the Core Module of the GEQ to evaluate their gaming experience.

4.4. Measures

To evaluate the validity of the questionnaire and its algorithm, two instances of the Game Experience Questionnaire (GEQ) were used. The GEQ is a self-report measure that presents questions (in the format of a Likert Scale) that ask the user to evaluate the experience they partook in. For this study, we used the GEQ - Core Module (composed by 33 questions), which focuses on different components of the gaming experience (Table 2) [5]. The version of the GEQ that was utilized was a Portuguese translation provided by the NeuroRehabLab of the University of Madeira.

Table 2. Valences of the GEQ and its definitions

GEQ valences	
Challenge	Measures the stimulation players perceive and the amount of effort they have to put into the game.
Competence	Refers to how successful and skilful people feel while playing.
Flow	Indicates the experience of being absorbed into the game world.
Immersion (Sensory and Imaginative)	Measures the experience of being surrounded by the game as a result from the interest in and appeal of the sensory and imaginative qualities of the object.
Positive and Negative Affect	Measures players' fun and enjoyment of the game, and the degree to which players are feeling bored and distracted, respectively.
Tension/Annoyance	Measures the degree to which players feel frustrated and annoyed.

5. Results

All of the 17 participants completed both instances of the GEQ. Overall, the experience was considered to be more positive for the game that matched the player's personality than for the videogame that was picked at random.

To better understand how the games were being perceived among participants, GEQ valences were split into two groups: positive valences that indicate that the gaming experience was positive, and negative valences, which mean that, the higher the score for them, the less participants enjoyed playing the videogame. For the positive valences, we considered flow, immersion, positive affect, competence and challenge. For the negative ones, we considered negative affect and tension/annoyance.

The GEQ asked players to rate their gaming experience according to a Likert Scale ranging from 0 (“Not at all”) to 4 (“Extremely”) [7]. We calculated the total sum for all the questions: we added the values from 0 to 4 for each of the questions referring to a positive valence and subtracted the values from 0 to 4 for those referring to a negative valence. We did this for both instances of the GEQ, and then we calculated the distance between the sums for the two games for each participant.

When taking a closer look at all the valences (therefore considering the entirety of the core module of the GEQ), 10 of the participants had a better experience with the game that suited their personalities while 7 of the participants preferred their experience with the randomly selected game. The average distance between the sums of the GEQ scores of the two games is of 22.588 (standard deviation: 18.977). When comparing the means of the answers for all the questions, 23 out of the 33 GEQ questions validated the hypothesis that the game that matches the user’s personality offered participants a better gaming experience than the random game.

If we focus solely on positive/negative affect, 12 participants claimed that their experience with their assigned game was better than their gaming experience playing the randomly picked game, and only 5 participants found that the random game suited them better. The average of the distances of the sums between the two games is of 6.294 (standard deviation: 5.924).

The comparison of the GEQ results for these valences for each of the two games (Figures 1 and 2) allow us to draw further conclusions. For positive affect (“I felt content”, “I thought it was fun”, “I felt happy”, “I felt good”, “I enjoyed it”), the game that, according to the algorithm, matches the user’s preferences always obtained feedback more positive than the random game (there is a higher percentage of answers above 3, and a smaller percentage of answers of 1 or under). On the other hand, for the negative affect (“It gave me a bad mood”, “I thought about other things”, “I found it tiresome”, “I felt bored”), participants claimed to be bored, distracted, or tired from playing the game more often during their gaming experience for the random game than for the game that was assigned to them through their preferences.

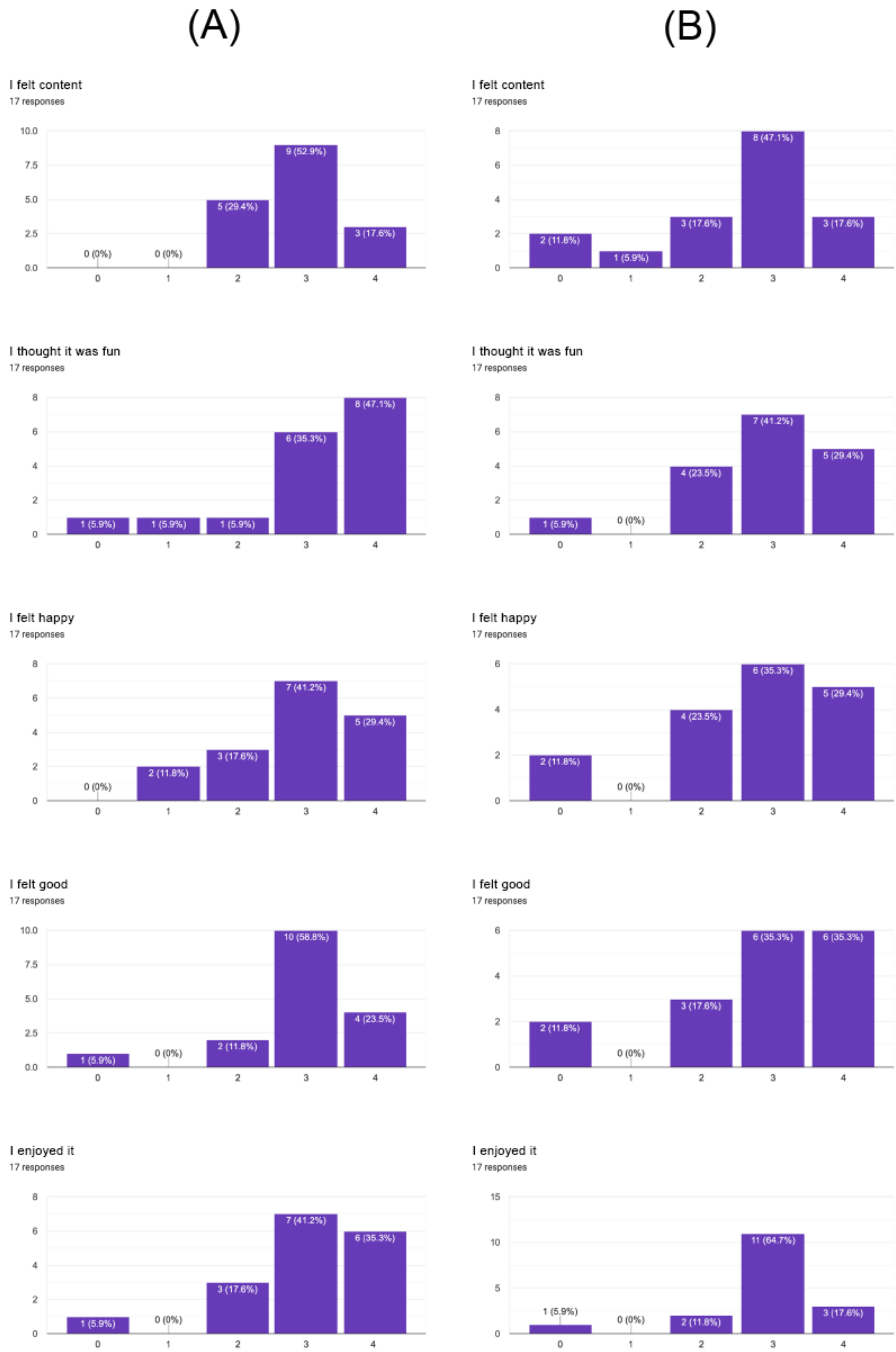

Fig. 1. GEQ answers for the positive affect valence. A) Game that matches the user's personality; B) Game randomly picked by the algorithm.

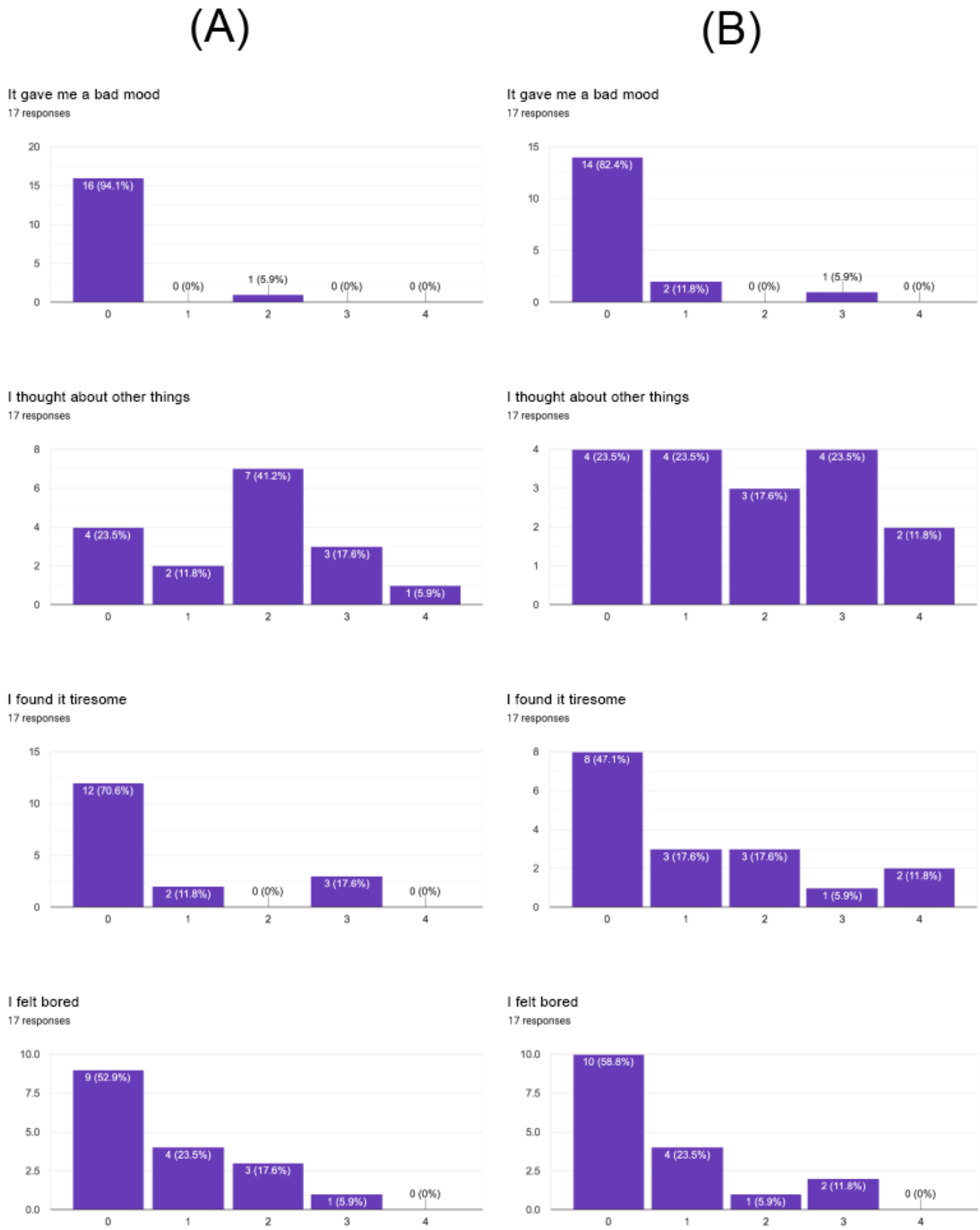

Fig. 2. GEQ answers for the negative affect valence. A) Game that matches the user's personality; B) Game randomly picked by the algorithm.

Additionally, only one user had an experience that could be considered negative (the sum of their GEQ responses was equal or lower than 2). Meanwhile, for the randomly picked game, 2 participants rated their experience as being negative.

Upon taking a closer look at the participants' characteristics that culminated in different GEQ scores, we looked into how the participants' gaming habits influenced how open they were to a gaming experience and, consequently, how they felt about it regarding their enjoyment. This said, considering the positive/negative affect valences for frequent players (people who play games every day or, at least, on a weekly basis), the average GEQ sums for their preferred game (the game they enjoyed the most, independently of it being the one that matched their personality) was 14.64 points. For people who had less gaming habits (occasionally, rarely or never played videogames), the average GEQ sums for their preferred game was 12.75, which indicates that people who are frequent gamers are more open to gaming than those who are not as familiar with videogames or do not game as much. The same difference was found in the game that the participants enjoyed less (once again, independently of it being the one that the algorithm selected or the one picked at random). Participants with gaming habits attained an average of 8.82 for the GEQ score for the game they enjoyed less, while participants that were not used to gaming scored an average of 7.13.

6. Discussion

This pilot study shows that, although not always, the game that matches the user's preferences usually offered an experience that the participants found more engaging, interesting, and immersive than the randomly picked game.

The results concerning how the participants perceived the experience for the random game were usually equally good and above the average gaming experience. The worst experiences are all linked to the game that was randomly picked. This means that, even if the game that was assigned by the algorithm to a participant did not fully match what they expected from a game, the experience was not an unpleasant one, as it could be seen in the graphics comparing positive/negative affect between games (Figures 1 and 2).

We argue that these discrepancies between what the participants expected (and, therefore, what would supposedly match their actual preferences) and the game that the algorithm said that matched their personality and gameplay preferences stem from the weights attributed to each question of the questionnaire, as this influences the final outcome and how user's responses are analysed. If the participants answered to most questions in one direction but, in one of the ones bearing the most weight, answered something that was different from what they expected (*e.g.*, a specific genre that usually does not embody characteristics they favoured in other questions), the game that the algorithm concluded that matched them could be a different one from what the participant had anticipated. Additionally, it is imperative to underline that, even if genres are a way to group videogames into categories, videogames of the same genre can be immensely different from one another in terms of how gameplay is tackled or explored, hence further contributing towards the discrepancies found in this pilot study.

As explored in the previous section, also hypothesize that lower sums on both GEQs might be attributed to cases where the participants had little to no gaming habits. Participants who claimed they had gaming habits of playing videogames every day or every week attained higher GEQ scores on their preferred game, independently of it being the one that was attributed to them by the algorithm or the one that was randomly selected. Interestingly, even for the game they enjoyed less, the GEQ scores were higher than those obtained by participants who never gamed or only played videogames on occasion.

Most participants claimed they had a positive experience playing videogames. When considering positive and negative affect for the game that matched the participants' preferences, only one user had an experience that could be considered negative (the sum of their GEQ responses was equal or lower than 2). Meanwhile, the participants rated their experience with the randomly picked game as less positive than the one they had with the assigned game, and two participants rated their experience as being negative.

Therefore, even if the algorithm fails to pinpoint the exact preferences of the participant, it is easier for the user to enjoy a videogame, independently of its genre, if the person has previous and frequent gaming habits and enjoys playing videogames.

One of the main limitations of the present study has to do with the size of the sample. Ideally, this study should be repeated with a larger sample. Another thing that was rather limitative in this study was the fact that participants only had 30 minutes each to play both games, which meant they spent no longer than 15 minutes playing a single game. Considering that the later stages of immersion (engrossment and total immersion) are only attained when the player reaches the level of engagement, this is, becomes comfortable enough with the game's commands that the human-videogame interaction feels natural [3], it is possible that their experience was not as complete and immersive as it could have been had they had more time to spend playing each of the two games.

Another limitation of this study has to do with the games that were analyzed and sampled, which was limited to a single game of each genre. To try and get around this issue, more videogames needed to be considered.

7. Conclusions

This pilot study had the objective of gauging the validity and the pertinence of using a questionnaire to predict user preferences in terms of videogames and their respective and unique gameplays, therefore resorting to small data. The results of the pilot study that are presented here were able to infer important findings within this topic, mostly of qualitative nature. The questionnaire successfully collected input in terms of player preferences that was posteriorly analyzed by the algorithm, in order to tell which kind of videogame would better suit an individual and their unique preferences.

Nevertheless, considering this level of detail is still an under explored field within the world of player type taxonomies and player preferences—particularly when it comes to serious games designed specifically for rehabilitation purposes—it is important for the community to engage in this kind of endeavor so this method can be validated not only with a larger sample but also among disabled population, who would be the main target of this questionnaire and algorithm.

Even so, this study allows us to conclude that using this approach to predict user videogame preferences is viable as, in most cases, the algorithm successfully predicted player preferences, as it was seen when GEQ results were compared between games—the game assigned to the participant that matched their preferences and the game that was randomly picked by the algorithm. This means that the questionnaire is collecting relevant data that allows this prediction to take place when comparing user responses to game characteristics' maps.

Considering that all the games contemplated in this pilot study are successful commercial titles within their genres, it is possible to attribute some of the success of the study to that aspect, since the game that was randomly picked by the algorithm generally got good responses in terms of user experience, although, in most cases, not as positive as the response users delivered when playing the games that had been assigned to them. Additionally, it is possible to conclude that, no matter the game, people with gaming habits will respond better to videogames than those that have no gaming habits.

With this in mind, it is possible to conclude that using this questionnaire somewhat allows game developers to infer not only which game genre, but also what kind of game characteristics (game perspective, game-play mode, game length, graphic style and level of player involvement required) work better for a particular user/group of users, which can prove to be a powerful tool when developing games for disabled people.

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