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An instrument to build a gamer clustering framework according to gaming preferences and habits

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ABSTRACT

In the era of digital gaming, there is a pressing need to better understand how people's gaming preferences and habits affect behavior and can inform educational game design. However, instruments available for such endeavor are rather informal and limited, lack proper evaluation, and often yield results that are hard to interpret. In this paper we present the design and preliminary validation (involving N = 754 Spanish secondary school students) of a simple instrument that, based on a 10-item Game Preferences Questionnaire (GPQ), classifies participants into four 'clusters' or types of gamers, allowing for easy interpretation of the results. These clusters are: (1) Full gamers, covering individuals that play all kinds of games with a high frequency; (2) Hardcore gamers, playing mostly first-person shooters and sport games; (3) Casual gamers, playing moderately musical, social and thinking games; and (4) Non-gamers, who do not usually play games of any kind. The instrument may have uses in psychology and behavioral sciences, as there is evidence suggesting that attitudes towards gaming affects personal attitudes and behavior. Besides, we propose applying the instrument to help designers of educational games to get better tailored their games to their target audiences.

1. Introduction

Digital games (hereafter 'games') have become a popular type of media, especially for new generations (Connolly, Boyle, MacArthur, Hainey, & Boyle, 2012; Garris, Ahlers, & Driskell, 2002). The increasing socioeconomic relevance of games has motivated different lines of research. One of the topics that has recently attracted researchers' interest is the relationship between gaming and behavior (Bavelier et al., 2011). This includes research on how playing games modifies game players' (hereafter 'gamers') behavior *outside* the game world (Elson & Ferguson, 2014), but also how personal attitudes and traits influence behavior *inside* the game (Giannakos, 2013; Hainey et al., 2013; Hamlen, 2011). A study led by Veronica Zammitto (Zammitto, 2010) suggests that the gaming preferences of gamers are connected to their personality. Moreover, Zammitto concluded that there are personal traits influencing the types of games a player may be inclined to buy.

Surprisingly, there are no validated and widely accepted frameworks to support and unify this kind of behavioral research on games. Researchers need to develop their own instruments and methodologies to measure aspects related to gaming behavior, hindering development of new research breakthroughs based on meta-analysis and limiting the soundness of the conclusions obtained. Measuring gaming preferences and habits is a relevant example, as this is often needed in this type of research, but the instruments available for such purpose are incomplete, not fully validated, too complex to apply, or too complex to interpret once applied.

A different line of research in games analyses their potential as educational tools. The engaging nature of games and the hypothesis that gamers might actually be developing useful skills (Subrahmanyam & Greenfield, 1994) led different authors to propose that games can improve traditional educational approaches (Gee, 2003; Hwang, Wu, & Chen, 2012; Papastergiou & Solomonidou, 2005; Sung & Hwang, 2013), giving origin to what we know as educational games. However, research into the

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effectiveness of educational games has yielded mixed results (Connolly et al., 2012; Hays, 2005; Ketelhut & Schifter, 2011), partly due to poor alignment with the characteristics of the intended audience.

Understanding the intended audience is key for successful educational game design. When the target population for an educational game is not researched in due form before starting the game design, the outcome is usually a bad game that does not meet the audience's preferences and is incapable of competing with entertainment games (Facer, Furlong, Furlong, & Sutherland, 2003; Kinzie & Joseph, 2008). Gaming preferences and habits are, again, a key aspect in this context, as it determines what type of game may be more appropriate for the intended audience. Therefore, the aforementioned lack of unified and validated instruments for measuring this construct is also a barrier for educational game research.

In this paper we propose and validate the *Game Preferences Questionnaire* (GPQ), an instrument to measure the game preferences and habits of an intended audience. The instrument is easy (and quick) to administer, having only 10 Likert-scale items, and produces a classification of the participants into four discrete profiles (or clusters). This facilitates interpretation of the results, as categorizing entities based on their common characteristics allows for faster cognitive processing of complex systems, a motivation that underlies psychological typologies (C. Bateman, Lowenhaupt, & Nacke, 2011).

The clusters that each gamer can be assigned to by the instrument are as follows: (1) *Well-rounded gamers*, covering individuals that play all kinds of games with a high frequency; (2) *Hardcore Gamers*, covering individuals that play mostly First Person Shooters (FPS) and sport games; (3) *Casual Gamers*, who play moderately musical, social and thinking games; and (4) *Non-Gamer*s, including individuals that do not usually play games of any kind.

As users belonging to different clusters tend to prefer different types of games, this instrument could help researchers better tailor their educational game designs to the intended audience, and also add valuable information to studies dealing with users' personality traits and behavior.

The present paper is structured as follows: the next section outlines the literature review; section 3 presents the development of the instrument while section 4 includes the validation process; section 5 presents the discussion, section 6 the limitations of this study and, finally, section 7 presents the conclusions and the future work. The full instrument, along with instructions on how to administer it and process the results, can be found in Annexes A and B.

2. Literature review

In this section we address different works that are relevant for our purpose. Sections 2.1 and 2.2 discuss taxonomies to classify games and gamers. Section 2.3 reviews instruments that are currently available to classify gamers.

2.1. Game classifications

There are multiple works attempting to classify games through different conceptualizations. Some works are rooted in the game industry sphere, while others are grounded in academia (Apperley, 2006; Ducheneaut, 2006; Elverdam & Aarseth, 2007; Klabbers, 2003; Lindley, 2003; Myers, 1990; Rollings & Adams, 2003). The most popular way of grouping games is by genre. Genres usually group games with the same gameplay interaction style rather than any visual or narrative differences. For example, games considered to belong to the First Person Shooter (FPS) genre are shooters regardless of whether the story is about space conquest or World War II.

There are many game classifications available and there is no consensus on the definition. For example, the Wikipedia games segmentation (Wikipedia, 2009) (a taxonomy generated and updated primarily by the community of gamers) includes, as of this writing, 14 game genres: Action, Sports, Racing, Platform, Music, Adventure, Role play, Survival horror, Simulation, Massively Multiplayer Online Game, Strategy, Puzzle, Traditional, and Educational. Lucas and Sherry (Lucas & Sherry, 2004) identified 13 game genres: Strategy, Puzzle, Fantasy/Role-playing, Action/Adventure, Sports, Simulation, Racing/Speed, Shooter, Fighter, Arcade, Card/Dice, Quiz/Trivia, and Classic board games. Studies by Van Eck (Eck, 2007), or Kirriemur and McFarlane (Kirriemur & McFarlane, 2004), reduce the genres taxonomy to six. Andrew Rollings and Ernest Adams did a thorough analysis of game genres in their book "On Game Design" (Rollings & Adams, 2003), and its revision "Fundamentals of Game Design" (Adams, 2010). These authors believe that in order to learn how to design a game, it is necessary to understand which foundational aspects are involved in the different game genres, of which they identify 10: Action, Strategy, Role-playing, Sports, Vehicle simulation, Construction and management simulation, Adventure, Artificial life, Puzzle, and Games for girls. The authors also recognize that there are some games that fall within more than one genre, however they warn that special care needs to be taken since such games might not be appealing for any of the genre audiences. The strength of Rollings and Adams' classification relies on their detailed explanation of the aspects involved in every genre, and how those affect game design. This work has received the support of the game community endorsing the book, and positive reviews from the specialized media.

Besides, from the different game genres classifications, many studies have evidenced that different users tend to prefer different types of video games. For instance, there are several studies showing the differences between boys and girls in their gaming preferences (Livingstone & Bovill, 1999; Sherry, Lucas, Greenberg, & Lachlan, 2006). As an example, Chou and Tsai (Chou & Tsai, 2007) found that males prefer playing sport games and car race games, including competition, action and entertaining 3D attributes, while females prefer adventure games, puzzles or card games, reflecting instructive attributes. Male students were more likely to agree on positive statements about the effects of playing computer games (e.g. increased creativity, eye-hand coordination, personal relationships) while female students agreed on negative statements (e.g. aggressive behaviours).

These studies show a strong inclination of different non-overlapping segments of the population (e.g. boys and girls) towards different types of games. This suggests that perhaps players could also be classified in disjoint groups according to their gaming preferences and habits. These classifications are covered in the next section.

2.2. Player profiles

Player profiles are a proposed construct to classify gamers according to the kind of games they prefer, or even related to the reasons for which they play. In fact, different genre models could be an indirect way of categorizing players. However, there is no consensus on this topic either. The following is a description of some such classifications.

2.2.1. By the games they play

Notwithstanding the lack of agreement, most classifications make the distinction between *hardcore* and *casual* gamers depending of what kind of games they play. In his book “A casual revolution” Jesper Juul (Juul, 2012) identifies Hardcore players as people who play as a lifestyle preference and invest substantial amounts of time and money on games. Casual players, on the other hand, prefer games that adapt to their lifestyle, usually playing on platforms they already own and that can be played in short sessions in between other activities. Kirman & Lawson (Kirman & Lawson, 2009) propose three categories, adding *peripheral players*, defined as those that only interacted with other players a handful of times. They are inactive and not a part of the community and can therefore be found at the very edge of the network. It is common to think that hardcore players play more and are more game-literate; Juul reveals that casual players also look for challenge in their games, accompanied by audiovisual rewards, and can also play for a long time, but split up into short sessions. A reference to hardcore and casual can be found in most of the game design books (Sotamaa, 2007). Unfortunately, in most cases, terminology is interpreted only as a skill ranking – with casual gamers considered clumsier than hardcore ones (McAllister, 2015).

Within the scope of online games, Mulligan and Patrovsky (Mulligan & Patrovsky, 2003) argue that players should actually be divided into three separate segments: hardcore, moderate, and mass-market. In this case, the moderate gamers are something between hardcore and mass-market (casual): they tend to spend substantial money on games but are wary of becoming as involved as hardcore gamers. According to Bateman and Boon, the audience model of Electronic Arts is actually very similar to the one introduced by Mulligan and Patrovsky. EA, however, refers to the moderate segment with the term *Cool Gamers*. This hypothetical split is primarily market-oriented and widely known in the game industry (C. M. Bateman & Boon, 2006). Market-wise, the genre system is based on a conception that certain players mostly buy games of a particular type.

2.2.2. By their play styles

A different way to classify players is by the behavior they exhibit while playing. The industry (C. M. Bateman & Boon, 2006) introduced one of the most comprehensive audience models found in the literature, with a typology that is publicly accepted and widely used among major U.S. game companies. They segmented players into four clusters corresponding to four strategies: *Conqueror play* focuses on winning and “beating the game”; *manager play* revolves around a strategic and tactical challenge, while *wanderer play* involves the search of enjoyment and fun experience. Strangely, authors said little about the fourth category, *participant play*.

Salen and Zimmerman (Salen & Zimmerman, 2004) introduced a player typology where player groups are defined by their relation to the rules of the game. Mulligan and Patrovsky (Mulligan & Patrovsky, 2003) introduced a grouping based on relations between players. While both these formulations can surely help designers to anticipate player behavior, they still remain relatively abstract and are based more on personal experience than empirical data (Sotamaa, 2007).

Nevertheless, the most thorough and influential model based on play-styles was introduced in 1996 by Richard Bartle. In its paper (Bartle, 1996), he introduced an informal, qualitative model characterizing players participating in the early online synthetic worlds known as MUDs (Multi-User Dungeons). That study helped other researchers to produce a test outputting four types: *Achiever*, *explorer*, *socializer*, and *killer*. However, the Bartle test has significant shortcomings that make it unsuitable as a general framework for player typology. The merits of Bartle's model are not limited to identifying the four things people typically enjoy in online worlds - he also discusses the dynamics between different player types. However, as remarked by Yee (Yee, 2006), the Bartle test was constructed for entertainment purposes, and was never intended to be a robust instrument. In a different study Yee (Yee, 2005) carried out a factor analysis for extracting key motivational dimensions in Massively-Multiplayer Online Role-Playing Games (MMORPGs). Based on data of 2300 users he identified ten independent, nonexclusive player motivations, grouped into achievements (advancements, mechanics, and competition), social (socializing, relationships, and teamwork) and immersion (discovery, role-playing, customization, and escapism). Yee's motivations of play model identified more diverse patterns than Bartle's informal report – an inevitable consequence of exploring a far greater range of motivational patterns. Nevertheless, neither the Bartle type model nor Yee's motivations were ever designed to function outside of the narrow context of massively multiplayer games.

2.3. Classification instruments

Despite the importance of player classification, we have not found any existing instrument to determine player typologies that could be used to improve the designing process in the context of educational videogames.

The only game classification instrument we were able to find was developed by Veronica Zammitto (Zammitto, 2010), based on Rolling and Adams' (Rollings & Adams, 2003) classification. The primary hypothesis of her work was that people with certain personality traits would prefer certain video game genres. During the process of supporting her hypothesis, she proposed a gaming preferences questionnaire to classify players, and explored the relationship between personality traits and game preferences. The questionnaire sought to collect information to measure what gamers prefer about games, and thus which game genres they prefer. Nevertheless, Zammitto's questionnaire is mainly oriented towards users' stated gaming preferences, and it does not take into account users' gaming habits, such as gaming frequency. Moreover, it is oriented to study the relationship between gaming preferences and players' personality rather than clustering the players according to their actual gaming preferences.

A recent study by Hainey et al. (Hainey et al., 2013) compared the time spent playing videogames of students from Scotland and the Netherlands, and concluded that on average, students spent 9–10 h per week. Hamlen (Hamlen, 2011) also researched the time that children typically spent playing videogames using a survey. Ip et al. (Ip, Jacobs, & Watkins, 2008) even found evidence revealing that examination marks are negatively correlated with gaming frequency - i.e. frequent gamers generally achieve lower marks than less frequent gamers. Therefore, it seems that gamer segmentations should factor in the time spent actually playing games.

As we have shown in this section, many researchers agree that identifying different gaming profiles can contribute to game design by providing information on the motivational, aesthetics or cognitive styles that gamers prefer to find in their games. Nevertheless, if we are to achieve that goal, first we need reliable classification instruments.

3. Development of the instrument

This section briefly describes the development of the instrument to classify players according to their gaming preferences and habits, a proposed construct for characterizing how a person uses digital games, including the types of games they enjoy the most and how often they play. We measure it via two indirect constructs: (1) gaming frequency and (2) gaming preferences, using a questionnaire (GPQ) scored on a 7-point Likert scale.

Although there is no consensus on the best scale size to be used in Likert questionnaires, we chose to use a 7-point scale based on the number of items and the available literature. The psychometric literature suggests that the more scale points the better but points at diminishing returns after around 11 points (Nunnally, 1978). This led us to rule out 10-point scales or above, leading to a single choice between 5 and 7-point scales. According to Krosnick and Presser (Krosnick & Presser, 2010), for a 10-item questionnaire both 5 and 7-point scales are appropriate and their results should not differ vastly.

3.1. Gaming frequency

Gaming frequency is measured using Item 1, to be answered on a 7-point Likert scale that ranges from “never” to “daily”:

Item1: How often do you play videogames?

As we have seen in the previous section, some studies have tackled the time spent by students playing videogames, and how these gaming habits could affect their academic performance. It seems clear that gaming frequency is a key factor when determining what kind of player is a particular student.

3.2. Gaming preferences

Gaming preferences are measured using Items 2–10 (see Annex A for exact questions), also measured on 7-point Likert scales.

Items 2–10. How much do you like the following types of games?

Table 1 summarizes video game genres, and examples included in the instrument. Respondents indicated their liking of each genre by circling a 7 Likert-type response from 1 (strongly dislike) to 7 (strongly like).

This reduced game-genre list was arrived at after reviewing previous research (Funk, 1993; Rollings & Adams, 2003), gaming Web sites, industry reports and video game rental stores. Following Lucas and Sherry's (Lucas & Sherry, 2004) recommendations we included representative games of each genre to avoid ambiguity, making it easier for users to distinguish each category. Moreover, describing game types based on relevant examples is probably the only way to limit the bias introduced by subjective responses, as gamers are good at developing mental models of how much they may like a new game by establishing comparison to games they liked or disliked in the past. This approach also increments accuracy and facilitates instrument maintenance, as descriptions of game types are overly ambiguous. For example, some people may associate ‘adventure’ games to platform/action like games, while others may associate the term with slow-pace point-and-click adventures. However, the examples provided should be updated depending on the target population and to ensure they are still recognizable over time.

4. Validation/reliability

This section describes the process followed to produce the framework for classifying gamers taking the Game Preferences Questionnaire (GPQ), along with measures of validity and reliability.

The core process is the clustering algorithm described in section 4.3. We have used the K-Means algorithm to group gamers in such a way that those in the same group (a.k.a. cluster) are more alike to each other than those in other groups. K-Means requires researchers to specify the number of clusters to produce before running the algorithm. Section 4.3 also describes the process that we followed to choose 4 clusters, instead of more or less.

Each response to the GPQ results in a 10-item vector. Instead of feeding these vectors directly into the clustering algorithm, they are first processed using a dimensional reduction technique called Principal Component Analysis (PCA). Use of PCA allowed us to identify two variables that account for most of the variance in the sample out of the initial 10-item vectors (items in the questionnaire). This facilitates interpretation of the outcomes with minimum information loss, as it is easier to describe clusters in terms of two variables than in terms of 10. The dimensionality reduction process is described in section 4.2.

The data used for building the clustering framework was obtained through an experiment involving 754 students. This is briefly introduced in section 4.1.

4.1. Participants and experiment

The reliability and construct validity of the instrument (including clustering algorithm and PCA) was developed using data from a previous 3-month study that evaluated the game *La Dama Boba* as an educational tool (Manero, Torrente, Serrano, Martínez-

Table 1
Video game genres and descriptions.

Genre	Description	Examples
First person shooter (FPS)	Games that emphasize shooting and combat from the perspective of the character controlled by the player	Call of Duty (Black Ops), Borderlands, Halo, BioShock.
Adventure or thrillers (ADV)	Games where you go on an adventure	Uncharted, Heavy Rain, Resident Evil or Assassin's Creed.
Singing, dancing or playing instruments (MUSIC)	Games involving musical activities	Guitar Hero, Sing Star, Just Dance.
Fighting (FIGHT)	Games that focus on martial arts or hand-to-hand combat	Tekken, Mortal Kombat, Street Fighter
Invention or cognitive (THINK)	Games that test your knowledge	Brain Training, Trivial, Brain Academy
Strategy games (STRAT)	Games that focus on careful and skillful thinking and planning in order to achieve victory	Civilization, Age of Empires, StarCraft.
Sports, racing or simulation (SPORT)	Games emulating traditional sports or simulating aspects of a real or fictional reality	FIFA, PES, NBA Live, Gran Turismo, Need for Speed.
Social and casual (SOCIAL)	Games that involve intense social interaction with physically co-located players, in generally short sessions	Super Mario, Mario Kart, Wii Sports.
Internet collaborative (I-COL)	Games involving up to hundreds of players interacting with each other on the same persistent world in real-time	World of Warcraft, Farmville.

Ortiz, & Fernández-Manjón, 2015). The sample included responses to the GPQ of N = 754 high school students from 8 different schools in Madrid, Spain. The gender proportion was 54.64% males, and 45.36% females. The median age was 14. By schools, 3 were private or chartered schools (48.8% of the participants), and 5 public schools (51.2% of the participants). This sample is representative in terms of gender and school distribution of the student population in the Madrid region for this age (Comunidad de madrid, 2011; Ministerio de educacion, 2008).

Students filled the instrument before getting engaged in any educational activities planned in the experiment. Although 57 did not complete the activities because of technical problems (for example, an unexpected power outage in one of the sessions), their responses to the GPQ were valid and therefore included in the present analysis.

4.2. Principal components analysis (PCA)

We used IBM SPSS Statistics v19 to run principal components analysis (PCA) on the 10-item questionnaire (GPQ) that measured students' gaming preferences and habits of the students that participated in the study. The suitability of PCA was assessed prior to analysis. Inspection of the correlation matrix showed that all variables had at least one correlation coefficient greater than 0.3 (see Table 2 where all the significant correlations at the 0.01 level are highlighted). The overall Kaiser-Meyer-Oklin (KMO) measure was 0.803 ($p = 0.00$) with almost all individual KMO measures greater than 0.7 (exceptions were PF.FIGHT – 0.663 and PF.SPORT – 0.694), classifications of 'middling' to 'meritorious' according to Kaiser (Kaiser, 1974). Bartlett's Test of Sphericity was statistically significant ($p < 0.0005$) indicating that the data was likely factorizable.

PCA revealed two components that had eigenvalues >1.00 and which explained 33.85% and 20.95% of the total variance, respectively. Visual inspection of the scree plot (Fig. 1) indicated that two or three components should be retained (Cattell, 1966). Two components were retained for simplicity and to meet Kaiser's stopping rule, which states that only the number of factors with eigenvalue over 1.00 should be considered (Brown, 2009). In addition, a two-component solution met the interpretability criterion.

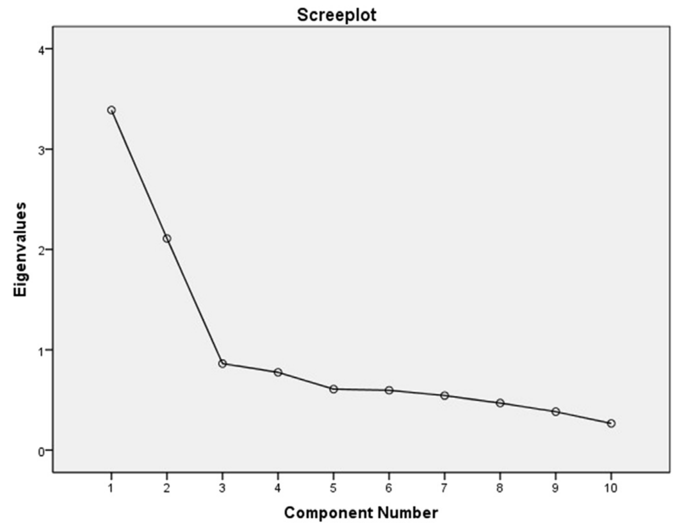

Fig. 1. PCA's scree plot.

The two-component solution explained 54.967% of the total variance. A Direct Oblimin rotation was employed to aid interpretability. The rotated solution exhibited met Thurstone's criteria for simple structure (Thurstone, 1947). The interpretation of the data was consistent with the attributes of the questionnaire and current state of the art, which suggest the existence of two different components related to gaming habits and preferences – echoing the casual vs. hardcore division identified in Section 2.2. Pattern matrix and communalities of the rotated solution (presented in Table 3) show that adventure games, first person shooters, fight, sport, internet collaborative games, and gaming frequency are strongly represented by component 1, while component 2 represents social, thinking and musical games. Strategy game habits seem to be hardly predictable by 2 component reduction. Correlation between components was proven to be positive and statistically significant.

Table 2
Pearson's Correlations between items. N = 754.

Correlations matrix											
		FR	FPS	ADV	MUSIC	FIGHT	THINK	STRAT	SPORT	SOCIAL	I-COL
FR	*Corr**	1									
	*Sig***										
FPS	*Corr*	0.584	1								
	Sig	0									
ADV	*Corr*	0.495	0.651	1							
	Sig	0	0								
MUSIC	*Corr*	−0.27	−0.457	−0.226	1						
	Sig	0	0	0							
FIGHT	*Corr*	0.371	0.517	0.474	−0.149	1					
	Sig	0	0	0	0						
THINK	*Corr*	−0.105	−0.163	0.002	0.318	0.094	1				
	Sig	0.004	0	0.959	0	0.01					
STRAT	*Corr*	0.123	0.211	0.367	0.021	0.3	0.41	1			
	Sig	0.001	0	0	0.565	0	0				
SPORT	*Corr*	0.358	0.447	0.398	−0.18	0.326	0.032	0.208	1		
	Sig	0	0	0	0	0	0.375	0			
SOCIAL	*Corr*	−0.073	−0.231	0.001	0.456	0.013	0.37	0.254	−0.016	1	
	Sig	0.046	0	0.976	0	0.724	0	0	0.669		
I-COL	*Corr*	0.328	0.288	0.323	−0.007	0.381	0.107	0.329	0.185	0.194	1
	Sig	0	0	0	0.853	0	0.003	0	0	0	

*Correlation; ** Sig(2-tailed).

Table 3
Component loadings of each component and communalities.

Component loadings of each component and communalities				
Item	Pattern matrix		Communalities	
	Component		Initial	Extraction
	#1	#2		
PF.FPS	0.830	-0.312	1.000	0.782
PF.ADV	0.802	0.004	1.000	0.643
PF.FIGHT	0.712	0.107	1.000	0.519
FR	0.708	-0.181	1.000	0.532
PF.SPORT	0.607	-0.024	1.000	0.338
PF.I-COL	0.549	0.321	1.000	0.406
PF.SOCIAL	-0.037	0.767	1.000	0.589
PF.THINK	0.034	0.746	1.000	0.558
PF.MUSIC	-0.376	0.653	1.000	0.565
PF.STRAT	0.477	0.551	1.000	0.534

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization; rotation converged in 5 iterations.

4.3. Clustering

We run a K-means clustering algorithm to classify users into different categories depending on their gaming habits and preferences. We used the two main components extracted from the PCA (see previous section) as input variables. As linkage criterion, we used the within-groups method and, to determine distance between cases, we selected squared Euclidean distance.

The K-means clustering algorithm requires, as an input, the number of output clusters to produce. To find the optimal number of clusters K, we followed the standard practice of generating all possible classifications, ranging from K=N (a cluster for each of the N samples) to 1 (a single cluster for all samples). We then applied the turning point location criteria to inform our decision, along with our understanding of how gamers have been informally classified in the past. Using this criterion, the most reliable number of clusters is located in the range from K = 3 to 6 (see Fig. 2). In the next steps, we examine cluster composition to determine the best value for K from within these options. Fig. 3 shows the composition of clusters when classifying samples into K = 3, 4 and 5 clusters. For each K, we then analyze each clustering based on its consistency and explanatory power.

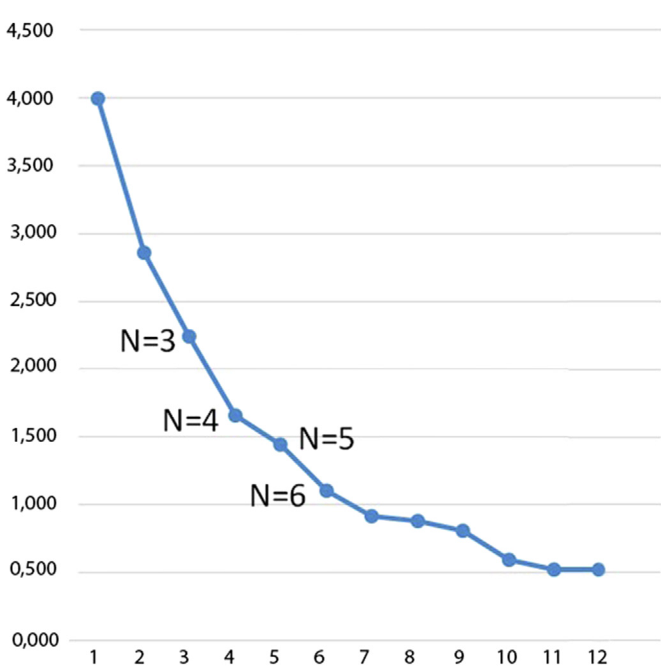

Fig. 2. Number of clusters vs. reliability. The turning point is located between K = 3 and 6.

4.3.1. 3 Clusters

When selecting 3 clusters, the main problem is that none of the generated clusters provides a good fit for gamers that play little or no videogames. It is hard to believe that even in this particular age group all participants would be interested in games. As shown in Fig. 3, the game frequency in two of the three clusters is quite high, but, in the remaining, shadowed cluster, frequencies range from none to high. For this group it becomes difficult to explain the behavior of its members as a whole. For this reason, we decided to discard a 3-cluster classification.

4.3.2. 4 Clusters

We compared the 4-cluster classification to the 3-cluster classification, and the main difference is that in the 4-cluster classification the cluster with low gaming frequency members (top-left corner of Fig. 3, shadowed) is split into two clusters. The first of these groups represents people playing, with moderate frequency, mostly social, music, thinking and strategy games. The second group involves to users with no interest in videogames and with a very low playing frequency. Therefore, this classification provides a better fit for users that are not interested in games.

4.3.3. 5 Clusters and beyond

In the 5-cluster classification we also found it difficult to clearly describe the boundaries between groups. In particular, the first two groups showed (top-right corner of Fig. 3, shadowed) for 5-clusters turn out to be very similar. Both groups involve individuals with moderate playing frequency, and they choose to play the same type of games except for internet collaboration (which is present just in the second group). The 5-cluster approach was discarded because the limits between groups become increasingly blurred, while not providing significant additional explanatory power. This issue gets further accentuated in classifications with more than 5 clusters.

We have therefore adopted the 4-cluster classification since it seems to reflect the spectrum of gamers accurately and the boundaries of the groups are easier to describe and explain. In the next section 4.4, we describe each cluster by exploratory analysis of its main features, and analyze its relationship with the 2 principal components found with PCA.

4.4. Clusters definition

Table 4 shows a descriptive analysis of users according to the cluster they belong to and their game preferences and gaming frequency. Fig. 4 displays the cluster region based on the principal components found in PCA.

Using Table 4 and Fig. 4 we describe the different clusters as follows:

4.4.1. Cluster 1: casual

Users include in this cluster show a slightly below-average game frequency – with a Cluster Mean (CM) of 3.65 compared to a General Mean (GM) of 4.29. Their gaming preferences are: Musical Games (CM = 5.42 compared with GM = 3.69), Social Games (CM = 5.89; GM = 4.77), Thinking games (CM = 4.10; GM = 3.16), Strategy Games (CM = 4.24; GM = 3.73), and in to a lesser extent, Internet Collaborative games (CM = 4.01; GM = 3.75), are the most preferred.

This group plays moderately, and prefers Musical, Social,

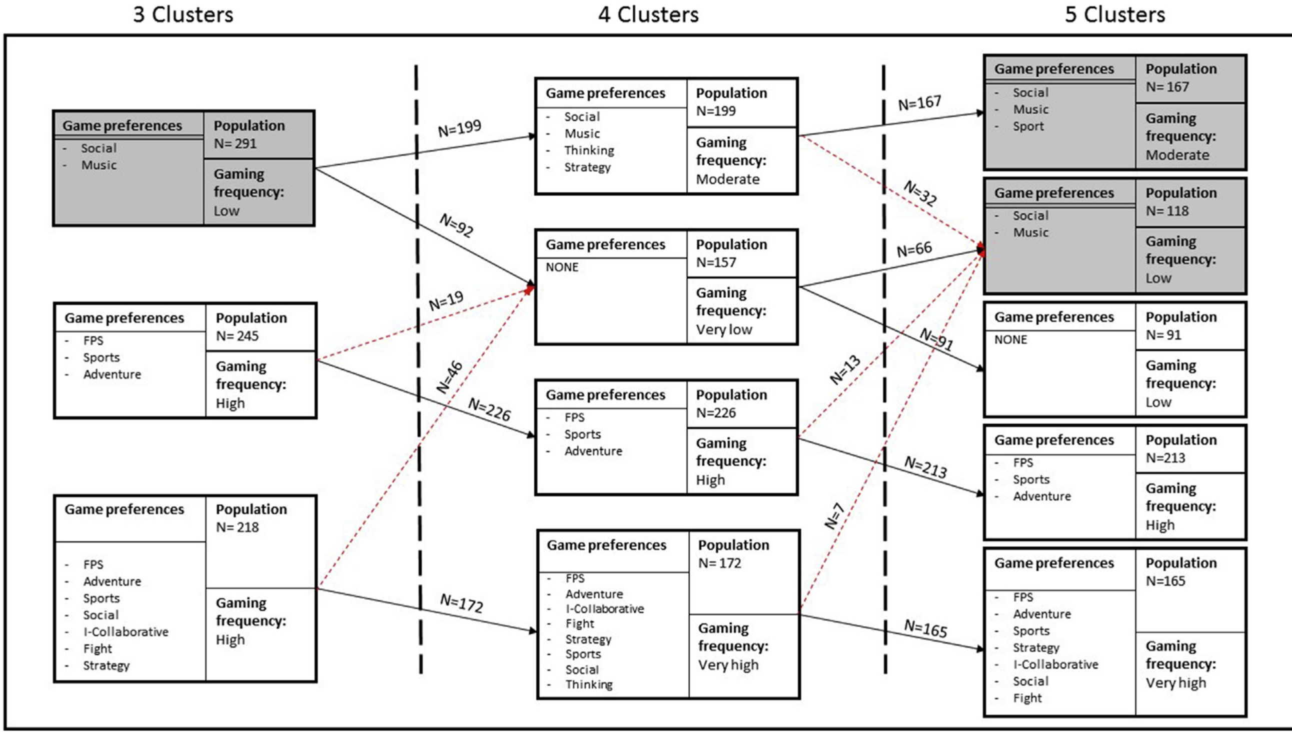

Fig. 3. Cluster composition when clustering into K = 3, 4 or 5 clusters, indicating migrations as K increase. Dashed lines are used for smaller contributions. Highlighted (darker) clusters are described below.

Table 4
Means comparative between clusters and items.

Items comparative by cluster											
Cluster		FR	FPS	ADV	MUSIC	FIGHT	THINK	STRAT	SPORT	SOCIAL	I-COL
1: Casual	Mean	3.65	2.71	4.07	5.42	2.83	4.10	4.24	4.71	5.89	4.01
	Std. Dev.	1.507	1.511	1.570	1.576	1.575	1.594	1.558	1.847	1.191	1.798
	Median	4.00	2.97	4.00	6.00	2.90	4.00	4.00	5.00	6.00	4.00
2: Non-gamer	Mean	2.58	1.61	1.88	4.30	1.49	2.69	2.20	2.59	4.68	2.20
	Std. Dev.	1.350	1.028	1.162	2.021	0.837	1.592	1.439	1.650	1.944	1.426
	Median	2.00	1.00	1.00	4.39	1.00	2.00	2.00	2.00	5.00	2.00
3: Hardcore	Mean	5.08	6.23	5.37	2.00	3.46	2.00	2.95	5.74	3.21	3.23
	Std. Dev.	1.542	1.209	1.695	1.376	1.854	1.162	1.783	1.718	1.727	2.051
	Median	5.00	7.00	6.00	1.00	3.00	2.00	3.00	7.00	3.00	3.00
4: WR gamer	Mean	5.55	6.29	6.25	3.36	5.10	4.01	5.55	5.89	5.58	5.55
	Std. Dev.	1.459	1.064	1.068	1.843	1.715	1.887	1.554	1.489	1.405	1.465
	Median	6.00	7.00	7.00	3.00	5.00	4.00	6.00	6.00	6.00	6.00
Total	Mean	4.29	4.35	4.50	3.69	3.26	3.16	3.73	4.85	4.77	3.75
	Std. Dev.	1.853	2.391	2.111	2.143	1.995	1.804	2.014	2.098	1.925	2.088
	Median	4.00	5.00	5.00	3.69	3.00	3.00	3.82	5.00	5.00	4.00

Thinking, Strategy, and Internet Collaborative Games. This description fits with what is commonly known as a **Casual** player. In Fig. 4, the Casual cluster borders with all other clusters: greater playing-time and game variety leads to the Well-rounded cluster, a preference for less-casual games to the Hardcore cluster, and less play-time to the Non-gamer cluster.

4.4.2. Cluster 2: non-gamer

This cluster includes people who do not play videogames, or do so with very low frequencies. Their gaming frequency falls far below the general median (CM = 2.58 compared to GM = 4.29). They only like Music games (CM = 4.30; GM = 3.69), scoring above the general mean, and Social games (CM = 4.68; GM = 4.77), scoring similar to GM. They dislike other game types, with cluster means for those games far below the general mean.

This group does not play videogames, and when they do, they mostly prefer musical and social games. We name this group **Non-gamer**. Increasing play-time would result, according to Fig. 4, in entering either the Casual or Hardcore clusters, depending on the chosen game types.

4.4.3. Cluster 3: hardcore

All users included in this cluster show a game frequency above the general frequency (CM = 5.08 compared to GM = 4.29). Their gaming preferences are: FPS Games (CM = 6.23; GM = 4.35), and to a lesser extent, Sports (CM = 5.74; GM = 4.85) and Adventure Games (CM = 5.37; GM = 4.50). Fighting games (CM = 3.46; GM = 3.26) present a mean similar to general mean. The rest of the genres are below the general mean.

We could say that this group plays FPSs very frequently, and

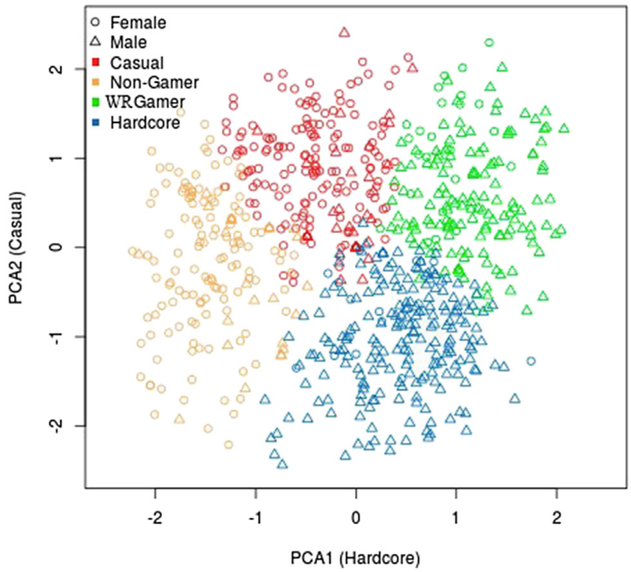

Fig. 4. Scatterplot of N = 754 participants according to PCA1 and PCA2, colored by cluster. Gender is encoded by symbol shape.

Sports and Adventure Games frequently. They do not like other games. This description fits with what is commonly known as **Hardcore** player. In Fig. 4, it can be seen to border with all other clusters: greater game-variety would lead to the All-gamer cluster, a shift towards casual games to the Casual cluster, and greatly reducing play-time, to the Non-Gamer cluster.

4.4.4. Cluster 4: well-rounded (WR) gamers

The users included in this cluster show a game frequency far above the general frequency (CM = 5.55 compared to GM = 4.29). Indeed, this is the most frequent playing cluster. Their gaming preferences are very wide: FPS (CM = 6.29; GM = 4.35), Fighting (CM = 5.10; GM = 3.26), Strategy (CM = 5.55; GM = 3.73), Adventure (CM = 6.25; GM = 4.50) and Internet-collaborative (CM = 5.55; GM = 3.75) games are preferred (with a much higher score than the rest of clusters). Sports (CM = 5.89; GM = 4.85), Social (CM = 5.58; GM = 4.77) and Thinking (CM = 4.01; GM = 3.16) games are also above the general mean.

This group plays with a very high frequency, and likes every type of videogame (only Musical games are slightly under the general mean), while often preferring FPS, Fighting, Strategy and Adventure Games. We name its members **Well-rounded gamers**. In Fig. 4, this cluster borders with the Hardcore and Casual clusters. The Hardcore cluster is reachable by reducing game variety, while the Casual cluster would imply reducing both play-time and game variety.

5. Discussion

When running PCA, we reached two main components related to game preferences and play frequency. After checking what games are mainly represented by each component, we named them “*Hardcore*” and “*Casual*” components. As shown in Table 4 and Fig. 4, the Hardcore component is strongly present in FPS, Adventure and Sports games, with a high playing frequency; and negatively present in Musical and Social games. On the other hand, Casual component is strongly present in Social, Musical, Thinking and Strategy games, with a low playing frequency and negatively present in FPS games. Those relationships agree with the common knowledge of the field.

The four clusters defined could be explained also through Hardcore and Casual components as described in Table 5. Note that Table 5 can also be inferred from Fig. 4, where each cluster roughly corresponds to a quadrant.

5.1. Gender

Although it is not the goal of this paper, it should be noted that this distribution is strongly influenced by the gender of the participants, which was not considered for use during clustering. As shown in Table 5, Fig. 4 and the histograms in Fig. 5, Casual and Non-gamer clusters are mainly composed of females, while the Well-rounded and Hardcore clusters are mainly composed of males. These results are also consistent with the studies previously discussed in literature review section.

In spite of these results, and as we can see in Table 6 and Fig. 5, there is considerable overlap between both genders in terms of preferences, and approximately 10% of our population failed to follow the expected classification. In particular, the Casual cluster presents a high proportion of males in a female-dominated cluster.

6. Limitations of the study

Item 1 in our questionnaire is used to determine the frequency with which respondents play games. This frequency ranges from very frequent (found in those who play several hours per day) to somewhat frequent (found in those who only play sometimes during the weekend) to infrequent (those who have not played a game in the last year). A study by Blair and Burton (Blair & Burton, 1987) indicated that the cognitive processes that respondents use vary depending on the relative frequency of the event. In other words, although it is easy to recall and count every instance for an infrequent behavior, it becomes more difficult to do so for a frequent behavior. Many researchers now maintain that in a survey situation in which respondents are asked a question relating to the frequency of a fairly frequent, non-salient behavior, they do not do a straightforward recall and count of every occurrence of the target behavior. Instead, they provide an *estimate* based on various inference strategies (Blair & Burton, 1987; Schwarz, 1999; Strube, 1989). This behavior and the fact that our instrument was self-reported by teenagers could affect the answers we obtained through our survey. Therefore, monitoring the gaming frequency and habits of the respondents, and comparing those results with their answers would provide robustness to our instrument.

Our genre-preference survey questions (items 2–10 in the GPQ) will need to be constantly revised in order to stay relevant; and, in particular, the lists of games as genre examples should be chosen so as to be highly recognizable by the target demographic; because such examples are critical to address the lack of a generally agreed-upon, unique taxonomy to identify games by genre. However, continuous changes in the videogames industry and player demographics result in a significant variability as to the evolving popularity of games and genres in each cultural context. Our sample experiment took place in Madrid, and therefore our results are only representative of this region. Students from other countries may find it difficult to identify our chosen game genres or the sample games used to illustrate each of them; or, due to socio-economical factors such as broadband availability, may have limited or expanded access to gaming in general, and/or certain game-genres in particular. In addition, our instrument was targeted at younger participants (under 20 years old). Older demographics may struggle to recognize certain genres and games. Even though question formulation will need to be updated, and exact cluster bounds will vary for each surveyed population, we believe that the main PCA dimensions and cluster definitions can still be of significant use for educational game design; and, in the following section,

Table 5
Clusters from the point of view of PCA1 (Hardcore) and PCA2 (Casual) scores.

PCA2: Casual	PCA1: Hardcore	
	Low	High
High	1. **Casual** Plays musical, social and thinking game in moderation	4. **WR gamer** Plays all kinds of games frequently
Low	2. **Non-gamer** Does not play videogames much	3. **Hardcore** Plays FPS and sport games frequently

Fig. 5. Histograms of participant count according to PCA1 and PCA2, showcasing different distributions for female vs male participants. Note the existence of significant overlap in PCA2.

Table 6
Clustering distribution by gender.

Cluster	Clustering by gender		Ratio (F:M)
	Gender		
	Female	Male	
1. Casual	198	37	6.3:1
2. Non-gamer	48	5	10.6:1
3. Hardcore	6	92	1:16.3
4. WR gamer	20	173	1:9.7

we describe a proposal to adapt cluster bounds to particular player populations.

7. Conclusions and future work

This research was based on the studies of Veronica Zammitto (Zammitto, 2009, 2010), who argues that gaming preferences are directly related to personality traits. However, Zammitto's instrument did not seek to classify gamers, and it neither took into account users' gaming frequency nor grouped them based on their gaming preferences. In this paper, we have presented an instrument that allows quick classification of videogame players according to their gaming frequency and preferences into four clusters. Participants are only required to fill a 10-item Game Preferences Questionnaire (GPQ), which can be done in less than 5 min 754 students participated in the development and experimental validation of the instrument.

This work may help researchers to gain further understanding of students' gaming preferences and interests, and, therefore, to design educational games that are better tailored to their players. Use of this instrument could entail the following benefits for educational games:

- Before creating an educational game, the target population could be requested to fill in the GPQ. After clustering responses, a game designer could decide, for instance, to highlight storytelling and low-paced reflection aspects if most of the population lies within the Casual cluster; or to add faster action-based elements for an audience of Hardcore gamers.
- After the game has been used within an educational study, classifying the population that has followed a gaming educational approach could help researchers to understand the outcomes of a particular experiment. With this kind of information, a researcher could correlate the results of a concrete educational game with the gaming preferences of the students. As an example, an educational game classified as a Musical game may prove to work very well for Non-gamers and Casual players, while achieving much lower success with Hardcore gamers.
- Gaming preferences and habits could also add valuable information about people's personality. Thus, this kind of instrument could be included into some personality tests to gain insight on respondents.

Although our four-group classification is only focused on game frequency and preferences, it seems to be in good agreement with different gamer classifications in the literature. Even though our method is different from those focused on the style of play, the results are similar, yielding four different types of players similar to those in Bartle's (Bartle, 1996) approach. Furthermore, the division of players into four groups appears to be in accord with the informal gamer classifications we have found in the literature: (1) players that emphasize social, thinking and musical games with a moderate playing frequency (Casual gamers) (2) players who do not like any game and hardly ever play (No gamers); (3) players who like all sorts of games and play very frequently (Well-rounded Gamers); and (4) players that prefer FPS, fighting and sport games with a high playing frequency (Hardcore gamers). This, of course, does not mean that a casual player could not play frequently; indeed, both clusters share a border (see Fig. 4). As the aim of this paper is to create a reliable and simple-to-use instrument that provides useful information to empower further research, having data that is consistent with what we already know is gives us greater confidence as to the reliability of our approach.

Although most players follow gender stereotypes regarding game preferences, we have found a considerable overlap in the PCA2 dimension (the Casual score; see Fig. 5). Despite the large correlation between gender and clusters, 10% of participants fall outside their expected gender-associated clusters, as can be seen in Table 6. Furthermore, the per-cluster ratio of male to female participants varies greatly, and is expected to evolve over time within any given population. In this sense, our instrument can be used to track the evolution of such ratios over time or between different demographics. Additionally, while including gender data in the clustering process could result in greater classification precision, so could the inclusion of participant age-groups or other relevant demographic factors. We have chosen to consider these factors out of scope to yield greater instrument generality, but other researchers can easily extend our results by adding such factors.

Our self-report survey (the GPQ) is designed to be quick to complete, allowing a fast assessment of the target population. The GPQ can be filled in less than 5 min, while obtaining enough data to subdivide a target population into well-defined groups, thus providing a broad vision of player preferences. In order to facilitate the use of our instrument, we have included in Annex B a step by step use recommendations and a usage example.

We consider that the proposed instrument opens a new way of classifying gamers, and believe it can encourage future discussions on gamer characterization and segmentation while raising awareness on the use and effectiveness of gaming profiles. Whether an applied game met or failed expectations, this instrument can provide important clues on the effectiveness of its targeting and design.

7.1. Future work

As a new instrument, more research is needed for fine-tuning and in-depth testing. While the current questionnaire appears to be effective, it may benefit from including additional survey items to achieve better gamer profiling. Additionally, experiments with broader population samples would allow us to refine the tool. In particular, and in order to explore the instrument's generality, we will conduct an experiment involving a population with a different background, age, socio-economical status and nationality.

When using the instrument as described in Appendix B, the clusters returned will be those described in this experiment, regardless of the difference in context as described in the Section 6 (limitations). We plan to add a web service to recalculate clusters automatically for a given set of tabulated responses, which would allow the instrument to automatically adapt to new populations of gamers. Additionally, the existence of such a web service would significantly lower technical barriers to instrument adoption, as potential instrument users would no longer need to perform their own cluster-centroid distance calculations.

A different line of research would entail using data from user game-play analytics to refine our classification. This could create a more complex taxonomy of players, including subgroups under each main cluster; or even allow fully-customized groupings to be generated after each experiment by automating most of the classification process (while leaving only the final step, of choosing a K that provides meaningful clusters, to analysts). Even without additional clustering, the analysis of users' gaming behavior could provide valuable insights on how each type of gamer prefers to play, and therefore on the mix of particular game mechanics that work best with each cluster, allowing the creation of games that are highly tailored to their demographics.

As we have seen, there are many studies that support that different game genres encourage different pedagogical aspects. Researchers have found differences suggesting that selecting educational games for combined classrooms of males and females requires careful consideration. Nevertheless, as of this writing, the connection between learners' attitudes (e.g., acceptance) for a game and their learning performance has not been well addressed. In this sense, in-depth analyses (i.e., behavioral sequential) should be conducted to understand how gamers' attitudes relate to their learning performance. In a recent study, Giannakos (Giannakos, 2013) suggests that attitudinal factors significantly affect knowledge acquisition from games, and his findings suggest that educators should provide a learning environment that fosters enjoyment in order to increase successful learning with games. We believe that, in the same vein, gamer profiles could shed light on the question of learning performance. We hope that use of this instrument will open a new approach to predict the learning outcomes of educational games, and will test this hypothesis by using it to analyze the impact of gamer profiles in users' learning performance through applied games.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.chb.2016.03.085.

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Annex A: Gaming Preferences Questionnaire (GPQ)

From 1 to 7, how often do you play videogames?								
		Never						Daily
FR		1	2	3	4	5	6	7
From 1 to 7, how much do you like the following types of games?								
Variable	Type of game							
		Never						Daily
PF.FPS	***First person shooters (FPS) games.*** *For example, Call of Duty (Black Ops) sagas, Borderlands, Halo or Bioshock.*	1	2	3	4	5	6	7
PF.ADV	***Adventure or thriller games.*** *For example, Uncharted sagas, Heavy Rain, Resident Evil or Assassin's Creed.*	1	2	3	4	5	6	7
PF.MUSIC	***Singing, dancing or playing instruments games.*** *For example, Guitar Hero sagas, Sing Star or Just Dance.*	1	2	3	4	5	6	7
PF.FIGHT	***Fighting games.*** *For example, Tekken sagas, Mortal Kombat or Street Fighter.*	1	2	3	4	5	6	7
PF.THINK	***Intelligence and quiz/trivia games.*** *For example, Brain Training, Trivial or Brain Academy.*	1	2	3	4	5	6	7
PF.STRAT	***Strategy games.*** *For example, Civilization sagas, Age of Empires or Starcraft.*	1	2	3	4	5	6	7
PF.SPORT	***Sports, Racing or simulation games.*** *For example, FIFA, PES, NBA Live, Gran Turismo or Need for Speed*	1	2	3	4	5	6	7
PF.SOCIAL	***Super Mario, Mario Kart o Wii Sports.***	1	2	3	4	5	6	7
PF.I-COL	***Internet collaborative games.*** *For example, World of Warcraft or Farmville.*	1	2	3	4	5	6	7

Annex B: Usage recommendations

In this section we provide steps and recommendations to facilitate the use of this player classification instrument without requiring familiarity with the underlying statistics. We will use the following abbreviations for each of the survey's 10 items: FR, PF.FPS, PF.ADV, PF. MUSIC, PF. FIGHT, PF.THINK, PF. STRAT, PF.SPORT, PF. SOCIAL and PF.I-COL (they are also listed in the first column of Annex A).

Step by step

1. Hand copies of the questionnaire (included in Annex A) to the population to classify, and ask them to fill it out. In our experiments, 5 minutes were more than enough to answer all 10 items.
2. Tabulate response data into a computer-readable format. We assume that each participant's response is encoded in a single row.
3. For each of the tabulated rows (participant responses), calculate its distance to each cluster's centroid, as defined by the means shown in Table 3, using the formulas below:

Distance to *Casual* Cluster:

$$\sqrt[2]{\begin{pmatrix} (FR-3{,}65)^2+(PF.FPS-2{,}71)^2+(PF.ADV-4{,}07)^2+(PF.MUSIC-5{,}42)^2+(PF.FIGHT-2{,}83)^2 \\ +(PF.THINK-4{,}20)^2+(PF.STRAT-4{,}24)^2+(PF.SPORT-4{,}71)^2+(PF.SOCIAL-5{,}89)^2+(PF.ICOL-4{,}01)^2 \end{pmatrix}}$$

Distance to *Well-rounded gamer* Cluster:

$$\sqrt[2]{\begin{pmatrix} (FR-5{,}55)^2+(PF.FPS-6{,}29)^2+(PF.ADV-6{,}25)^2+(PF.MUSIC-3{,}36)^2+(PF.FIGHT-5{,}10)^2 \\ +(PF.THINK-4{,}01)^2+(PF.STRAT-5{,}55)^2+(PF.SPORT-5{,}89)^2+(PF.SOCIAL-5{,}58)^2+(PF.ICOL-5{,}55)^2 \end{pmatrix}}$$

Distance to *Hardcore* Cluster:

$$\sqrt[2]{\begin{pmatrix} (FR-5{,}08)^2+(PF.FPS-6{,}23)^2+(PF.ADV-5{,}37)^2+(PF.MUSIC-2{,}00)^2+(PF.FIGHT-3{,}46)^2 \\ +(PF.THINK-2{,}00)^2+(PF.STRAT-2{,}95)^2+(PF.SPORT-5{,}74)^2+(PF.SOCIAL-3{,}21)^2+(PF.ICOL-3{,}23)^2 \end{pmatrix}}$$

Distance to *Non-gamer* Cluster:

$$\sqrt[2]{\begin{pmatrix} (FR-2{,}58)^2+(PF.FPS-1{,}61)^2+(PF.ADV-1{,}88)^2+(PF.MUSIC-4{,}30)^2+(PF.FIGHT-1{,}49)^2 \\ +(PF.THINK-2{,}69)^2+(PF.STRAT-2{,}20)^2+(PF.SPORT-2{,}59)^2+(PF.SOCIAL-4{,}68)^2+(PF.ICOL-2{,}20)^2 \end{pmatrix}}$$

4. Associate each participant with centroid that it is closest to; that is, for each participant, find the minimum distance to all four clusters, and associate it to the corresponding cluster.

Example usage

In Table 7, we will assume that two different individuals, A and B, have provided the following scores after filling in the questionnaire included in Annex A (steps 1 and 2 above).

	Survey items									
Individual	FR	FPS	ADV	MUSIC	FIGHT	THINK	STRAT	SPORT	SOCIAL	I-COL
A	6	4	5	4	6	4	6	7	3	4
B	3	1	2	5	3	6	2	1	5	4

TABLE 7. TABULATED QUESTIONNAIRE RESPONSES BY SAMPLE INDIVIDUALS A AND B.

We can now calculate the distance to each cluster by applying the formulas included above (step 3). The result is displayed in Table 8:

	Distances to each cluster			
Individual	*Casual*	*WR gamer*	*Hardcore*	*Non-gamer*
A	6,07	4,32	5,65	9,44
B	5,53	10,14	9,76	4,49

TABLE 8. DISTANCE TO EACH CLUSTER FOR SAMPLE INDIVIDUALS A AND B.
SHADED CELLS MARK THE LOWEST DISTANCES, AND THEREFORE, THEIR CLUSTERS.

These results lead us to include individual A in *Well-rounded gamer* cluster, and individual B in the *Non-Gamer* cluster.