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"I don't fit into a single type": A Trait Model and Scale of Game Playing Preferences

Gustavo F. Tondello[0000−0002−4174−7245], Karina Arrambide[0000−0002−1834−2346], Giovanni Ribeiro, Andrew Jian-lan Cen, and Lennart E. Nacke[0000−0003−4290−8829]

University of Waterloo, Waterloo, ON, Canada
gustavo@tondello.com, karina.arrambide@gmail.com, ggsribei@uwaterloo.ca, jin.lan.cen@gmail.com, lennart.nacke@acm.org

Abstract. Player typology models classify different player motivations and behaviours. These models are necessary to design personalized games or to target specific audiences. However, many models lack validation and standard measurement instruments. Additionally, they rely on type theories, which split players into separate categories. Yet, personality research has lately favoured trait theories, which recognize that people's preferences are composed of a sum of different characteristics. Given these shortcomings of existing models, we developed a player traits model built on a detailed review and synthesis of the extant literature, which introduces five player traits: aesthetic orientation, narrative orientation, goal orientation, social orientation, and challenge orientation. Furthermore, we created and validated a 25-item measurement scale for the five player traits. This scale outputs a player profile, which describes participants' preferences for different game elements and game playing styles. Finally, we demonstrate that this is the first validated player preferences model and how it serves as an actionable tool for personalized game design.

Keywords: Player traits · Player types · Player experience · Video games · Games User Research.

1 Introduction

The Games User Research (GUR) community has been collectively studying and classifying player preferences to understand what playing styles and game elements are enjoyed by what people. This knowledge can help designers create games better targeted to their audience, so they can offer their players the content they want [26, 36]; marketers segment their player base [15], so their campaigns can be more effective; and researchers explain the variables that influence the player's experience and enjoyment. This can also lead to the design of more effective games with a purpose, such as educational or health-related games. But despite the efforts of the community and the recent advances, we still lack a player preferences model that is backed by empirical evidence and a validated measurement instrument [15].

Given these shortcomings of the existing literature, we present and validate a player traits model with an accompanying measurement scale. More specifically, we build upon the research of Tondello et al. [35], which suggested the investigation of five player traits: action orientation, goal orientation, social orientation, aesthetic orientation, and immersion orientation. Their suggestion was based on the study of prior attempts to classify player preferences in types (e.g., [1, 26]). However, type theories have been criticized as inadequate in personality research, giving ground to trait theories [13, 23]. Trait theories interpret an individual as a sum of different characteristics, whereas type theories try to classify people in separate categories. But player type models rarely work in practice because people actually have several overlapping motivations, some weaker and some stronger. Rarely is someone motivated by a single factor. Therefore, trait theories have been suggested to also be a better approach to classify player motivations and behaviours in games [4, 15, 35]. In this context, the BrainHex [4, 26] was developed; a top-down player types model tentatively created to help understand player preferences and develop a definitive player traits model. Thus, Tondello and colleagues continued this line of investigation by analyzing the BrainHex data [26] and devising the five-trait player preferences model.

In the present work, we created a survey based on Tondello et al.'s [35] suggested five-trait model and validated its factor structure and content. We devised a survey with ten items per trait and collected data from 332 participants to validate it. Then, we conducted a factor analysis and a reliability analysis to retain the five items that contributed most to each subscale. Next, we conducted a confirmatory factor analysis with structural equation modelling to validate the final 25-item (five per trait) survey. Finally, we compared participants' player trait scores with their preferences for different game elements and game playing styles [36]. We found several significant correlations, demonstrating that the five player traits correspond to different playing preferences.

It is important to understand the relationship between personality, playing preferences, and enjoyment of game elements because this knowledge has uses in the design of targeted and adaptive games, as well as targeted multimedia advertising campaigns. Our research contributes to the HCI gaming community by shedding light on what playing styles are enjoyed with what specific game elements by what people. Our work introduces and validates a novel player traits model, with a standard 25-item survey to score people on the five traits. We also demonstrate that participants' scores in these five player traits help explain their preferences for different game elements and playing styles.

2 Related Work

Player motivations can be studied from three distinct perspectives: the general reasons why people play games, how people play different games, or how different game dynamics or mechanics motivate distinct player experiences. The present work and the extant literature reviewed in this section focus on the later topic. Thus, we are not concerned with why people play games, but rather with how they interact with and are more or less motivated by the diverse game dynamics that they experience. The objective of this research field so far has been to represent these preferences in player typologies. However, this paper aims to build a testable model of player traits instead of player types because traits can better represent the diverse range of playing motivations.

Caillois [9] was the first to present a typology of playful behaviour with four categories: *Agôn* (games of challenge), *Alea* (games of chance), *Mimicry* (playing as someone or something else), and *Ilinx* (visceral impact). Later, Malone's theory of motivating instruction [21] identified three categories of fun: challenge, fantasy, and curiosity. Based on these categories, a set of design heuristics was presented, where curiosity is used as an incentive to keep players engaged.

Bartle [1] presented the first modern player typology, which was based on two axes that represent players' interaction with the virtual world or with other players. In this typology, Achievers are constantly seeking to earn points or other virtual rewards in the game; Socialisers are focused in social interactions within the game and in forming relationships with other players; Explorers are interested in discovering and learning the game world; and Killers are focused in competitive game play and defeating other players. Bartle later expanded the model with a third dimension: whether the players actions are implicit or explicit [2]. However, Bartle never presented a validated measurement scale. Although many informal scales exist and are used online, they are more recreational rather than a scientific scoring system. Thus, it is not possible to confidently screen players using Bartle's typology or make assumptions about their gaming preferences.

Following a more systematic approach, the BrainHex [26] was developed, based on a series of demographic game design studies [3, 4] and neurobiological research [5]. It presents seven player types: Seeker (motivated by curiosity), Survivor (motivated by fear), Daredevil (motivated by excitement), Mastermind (motivated by strategy), Conqueror (motivated by challenge), Socialiser (motivated by social interaction), and Achiever (motivated by goal completion). A survey was conducted among more than 50,000 players establishing a relationship between them and the Myers-Briggs Type Indicator (MBTI) [25]. The BrainHex has been used in several studies to investigate players' motivation in games (e.g., [6, 28]). However, two independent studies [8, 35] found several issues related to its psychometric properties (factor validity, stability, and consistency). Additionally, the development of BrainHex was based on type theories, and particularly on the MBTI, which itself has several reliability and validation issues and is being replaced by trait theories in the psychology literature [23]. Therefore, the BrainHex scale cannot be reliably used to classify player preferences.

Yee et al. also employed a systematic approach throughout several studies [41, 44], ultimately leading to an analysis with over 140,000 participants of all game genres and the development of the gamer motivation profile [42]. In this model, 12 dimensions are grouped into six clusters: Action (destruction and excitement), Social (competition and community), Mastery (challenge and strategy), Achievement (competition and power), Immersion (fantasy and story), and Creativity (design and discovery). They also established correlations between these dimensions and personality traits [43]. This gamer motivation profile could be used to aid in the design of personalized games; however, its survey is a proprietary instrument, which makes it difficult to apply in every situation, especially for smaller game studios. On the other hand, we are making our measurement scale publicly available in this work; thus, it can be widely used by anyone.

Vahlo and Hamari [38] recently presented a five-factor inventory of intrinsic motivations to gameplay: Relatedness, Autonomy, Competence, Immersion, and Fun. Although their model is somewhat similar to ours because both introduce five different factors that motivate gameplay, their work is explicitly aimed at understanding the general motivations why people play games, without differentiating which gameplay activities they find more enjoyable. On the other hand, our work has the opposite goal of classifying the different gameplay styles preferred for each player, instead of the general reasons why they play games.

Hamari and Tuunanen [15] presented a literature review and a meta-synthesis of the existing player typologies. They identified five common constructs, which appear in some form in many of the available typologies: Achievement, Exploration, Sociability, Domination, and Immersion. Nonetheless, they also noted that not all models have been properly validated, that there are numerous methodological differences between them, and claimed for more research towards a definitive player preferences model. We answer this call in the present work.

2.1 The Proposed Model of Five Player Traits

As we mentioned before, the BrainHex was created as an interim model, aimed at providing the grounds for the development of a definitive player traits model. Building upon that work, Tondello et al. [35] conducted a series of analyses over the original BrainHex dataset [26]. The results showed that the BrainHex scale was only able to discriminate three types instead of the proposed seven: (1) *action orientation* (represented by the conqueror and daredevil archetypes); (2) *aesthetic orientation* (represented by the socializer and seeker archetypes); and (3) *goal orientation* (represented by the mastermind, achiever, and survivor archetypes). Furthermore, by inspecting the results and considering the existing literature on player typologies, Tondello and colleagues suggested that two additional traits should be considered, even though they were not originally captured by the BrainHex: *social orientation* and *immersion orientation*. The first, because social motivations are present in all existing player motivation theories, and the second because immersion is also a motivation listed in many existing theories [15] and evidence has been found that participants' attitudes towards story are related to their gaming preferences [35].

The present study builds upon Tondello et al.'s [35] work by introducing a new scale and providing evidence of the structural and construct validity of the player traits model, while also investigating player preferences for different elements of play and analyzing new player preferences data to provide a wider scope. This scale and its validation provide a more robust model for future applications. In summary, we base our work off the following player traits. Below, we also discuss some of the theoretical grounds for each proposed player trait, based on personality [10, 13] and motivation [11, 32] theories. However, it is important to note that these theories only partly explain the player traits, which were derived from data analyses from the aforementioned works, rather than from theory. Thus, it is not clear what other psychological factors influence them.

Social orientation: the player's preference for playing together with others online or in the same space. The motivation fostered by this kind of player experiences is explained by the psychological need for relatedness (the need to have meaningful interactions with others) discussed by self-determination theory (SDT) [11, 32, 33]. Moreover, people with more extraverted and agreeable personalities are usually more open to social experiences.

Aesthetic orientation: the player's preference for aesthetic experiences, such as exploring the game world and appreciating the game's graphics, sound, and art style. People are mainly motivated towards this type of gameplay by their openness to experience and the psychological need for autonomy [33], which is satisfied when the player can explore new paths and tailor their own journey.

Action orientation: the player's preference for challenging and fast-paced gameplay. As explained by SDT [33], this kind of experiences satisfies the psychological need for competence when the player can overcome the challenges.

Goal orientation: the player's preference for gameplay that involves completing quests or tasks, collecting digital objects, or similar experiences. This preference is also motivated by the psychological need for competence [33], but it is more focused on the amount or percentage of tasks completed, whereas action orientation is more focused on overcoming a few highly difficult challenges.

Immersion orientation: the player's preference for complex stories or narratives within games. This preference is also fostered by the player's openness to experience, but recent research has also showed that some people might simply be naturally more inclined to enjoy narratives [27].

2.2 Game Elements and Game Playing Styles

Tondello et al. [36] noted that past approaches to studying player types and preferences have ignored the relationship between those types and the activity elements of games. Those works focused only on high-level factors such as achievement or immersion. The issue with this is that it makes the application of those frameworks to the design of games difficult. Hence, Tondello et al. mapped constructs on an intermediate granularity level, commonly referred to as game dynamics or elements. In addition, they also investigated the different modes or styles of play such as a preference for single or multiplayer gameplay. These game playing styles can be combined with various game elements to create a variety of experiences. The game elements bore out by their work include strategic resource management, puzzle, artistic movement (such as music or painting), sports and cards, role-playing, virtual goods (dynamics of acquisition and collection), simulation, action (fast-paced play), and progression. The game playing styles found to be reliable were multiplayer (including cooperative and competitive), abstract interaction (such as from an isometric point of view), solo play, competitive community (such as streaming and e-sports), and casual gaming.

Similarly, Vahlo et al. [39] also provide a categorization of common game dynamics, structured in five factors: assault (dynamics of killing and murdering), manage (acquisition and development of resources), journey (exploration of the gameworld), care (showing affection and taking care of pets), and coordinate (matching tiles or music). In addition, they propose a clustering of player preferences based on their scored interest for each one of these groups of dynamics, identifying seven player types: mercenary, adventurer, commander, daredevil, companion, patterner, and explorer.

The five-trait model we propose and validate in this work is meant to address the building blocks of actionable game design. Therefore, we need to investigate if these player traits will correspond to participants' preferences for different elements of gaming. Thus, we compare participants' player traits scores with their preferences for game elements and playing styles from Tondello et al. [36], which we chose because their study considered a larger pool of game dynamics and identified a more diverse number of categories in comparison to Vahlo et al. The goal of this comparison is to validate the content of our player traits model and its usefulness for predicting player preferences.

3 Methods

We conducted an online survey between February and August 2018 using the Qualtrics platform provided by the University of Waterloo.

3.1 Survey Development

The player traits survey items were collaboratively developed by four researchers in two phases. In the first phase, we used a brainstorming approach to generate tentative items. First, each researcher studied the description of each of the five player traits from [35]. Next, each researcher wrote several suggested items that could be used to score someone on that trait. In the second phase, we put together all the suggested items from all researchers and collectively selected those that seemed the best. For the selection, each researcher read all the items available for each trait and voted for the items they thought would best represent the trait. Each researcher could vote on an unlimited number of items. In the end, the ten items per trait that received the highest amount of votes were included in the player traits survey. The complete list of items is presented in Table 1.

The online survey included the following sections. We used a 7-point Likert scale for all sections, except the demographic information, due to its prevalence in prior studies and its ability to detect subtle participant preferences.

1. Demographic information
2. Personality inventory (BFI-10 [29])
3. Player traits items (see Table 1)
4. Game elements preferences (the top three elements by group from [36])
5. Game playing style preferences (the top three styles by group from [36])

Table 1. All the player traits survey items.

#	Items
T1	I like to build or create new things or objects or characters in games.
T2	I like games with unique art styles.
T3	I often feel in awe with the landscapes or other game imagery.
T4	I like to customize how my character looks in a game.
T5	I like it when games have an element of exploration.
T6	I care more about gameplay than about graphics and sound. (R)
T7	The quality of the graphics and sound are really important for my appreciation of a game.
T8	I like to spend some time exploring the game world.
T9	I like it when games look unique or vibrant.
T10	I usually choose gear, weapons, or other game items based on what they look like.
I1	I like games which make me feel like I am actually in a different place.
I2	I enjoy complex narratives in a game.
I3	I like games that allow me to make decisions over the story.
I4	I like games with detailed worlds or universes to explore.
I5	I like it when I can be someone else in the game.
I6	I like games that pull me in with their story.
I7	I usually skip the story portions or the cutscenes when I am playing. (R)
I8	I feel like storytelling often gets in the way of actually playing the game. (R)
I9	Story is not important to me when I play games. (R)
I10	I like it when playing a game makes me lose track of time.
G1	I usually do not care if I do not complete all optional parts of a game. (R)
G2	I enjoy games that provide many optional goals for me to complete.
G3	I like games with lots of collectibles to find.
G4	I often start quests in games that I don't finish. (R)
G5	I am not concerned with whether or not I finish a game. (R)
G6	I feel stressed if I do not complete all the tasks in a game.
G7	I like to complete all the tasks and objectives in a game.
G8	I like completing games 100%.
G9	I like finishing quests.
G10	I ignore most side quests when I play games. (R)
S1	I like to interact with other people in a game.
S2	I often prefer to play games alone. (R)
S3	I like it when I have to collaborate with other players to solve a challenge.
S4	I don't like playing with other people. (R)
S5	I feel I can become friends with the people I play online with.
S6	I like to play online with other players.
S7	I like it when games require co-operation between players.
S8	I like games that let me play in guilds or teams.
S9	I don't enjoy multiplayer games. (R)
S10	I like it when games allow me to communicate to other players online.
A1	I enjoy highly difficult challenges in games.
A2	I usually play games at the highest difficulty setting.
A3	I like it when games challenge me.
A4	I like it when games get my heart beating fast.
A5	I like it when keeping my character alive is difficult.
A6	I usually avoid playing games at the highest difficulty setting. (R)
A7	I like it when progression in a game demands skill.
A8	I like easy games. (R)
A9	I like it when goals are hard to achieve in games.
A10	I like games that let me move at high speed.

Notes. Items marked with (R) were reversed for scoring.
The codes beside each item correspond to their position in the survey and the original intended trait for the item: T = Aesthetic, I = Immersion, G = Goal, S = Social, A = Action.

Regarding sections 4 (game elements preferences) and 5 (game playing style preferences) of the survey, Tondello et al. [36] classified player preferences in nine groups of three to 13 game design elements each, and five groups of one to six game playing styles each. But to score participants on these groups, we just asked them about their preferences for the three highest-loading game elements and playing styles for each group, as three items are usually enough to obtain a score for a latent variable.

3.2 Participants

We recruited participants through social media (Twitter, Facebook, and Reddit) and mailing lists. Participants were only required to be 15 years or older and have a working understanding of English. As an incentive, they were offered the possibility to enter a draw for one of two $ 50 international gift cards. In total, 350 participants completed the survey. However, we had to discard one participant who took less than five minutes to complete the survey (which we considered the minimum time to respond carefully according to our tests) and 17 responses that did not include answers to all the player trait items. Therefore, the final dataset contained 332 responses (212 men, 100 women, 11 transgender, 6 non-binary, and 3 identified as other). Participants were between 15 and 57 years old ($M = 25.7$, $SD = 7.1$).

Participants were from all continents, with the following distribution: North America (53.3%), Europe (27.1%), Asia (11.4%), Oceania (4.8%), South and Central Americas (3.0%), and Africa (0.3%). However, 318 participants (95.8%) reported a high English proficiency and 14 (4.2%) reported a medium proficiency. Therefore, we assume that language understanding was adequate.

Regarding game playing habits, 305 (91.9%) participants reported playing regularly on desktop or laptop computers, 240 (72.3%) play regularly on consoles, and 230 (69.3%) play regularly on smartphones or tablets. Moreover, 156 (47.0%) participants reported playing 1–10 hours per week, 101 (30.4%) play 11–20 hours per week, 72 (21.7%) play more than 20 hours per week, and only three (0.9%) participants reported playing less than one hour per week.

We also asked participants if they would be willing to complete a follow-up survey, which included only the player traits items, so we could calculate the test-retest reliability of the scale. 157 participants agreed to participate and were invited for the follow-up, but only 70 actually completed it. The follow-up surveys were completed between one and four weeks after the original responses.

4 Results

We present the study results with the following organization. First, we present the results of the initial factor analysis used to validate the traits structure and select the best five survey items per trait. Next, we present the results of the confirmatory factor analysis (CFA) used to evaluate the goodness of fit of the measurement model represented by the 25-item survey (five per trait), as well as the test-retest reliability analysis. Then, we discuss the player traits nomenclature and evaluate the correlations between them and with the Big-5 personality traits [13]. These analyses help to better understand the player traits and their meaning. Finally, we present the correlations of the player traits with participants' preferences for different game elements and game playing styles, which allows us to establish the model's usefulness for predicting gaming preferences.

For the factor analyses, we randomly split the dataset in two, so we could carry out the initial analysis and the CFA with different datasets. Therefore, the dataset for the initial factor analysis contained 175 responses (115 men, 49 women, 5 transgender, and 6 non-binary; $M_{age} = 25.6$, $SD = 7.1$). The dataset for the CFA contained 157 responses (97 men, 51 women, 6 transgender, and 3 other genders; $M_{age} = 25.8$, $SD = 6.9$). The number of responses in each group was not identical because of the random assignment to groups.

4.1 Initial Factor Analysis

We conducted an initial factor analysis with 175 responses to validate the trait structure and reduce the number of items in the survey. Our goal was to keep only the needed amount of items to enable scoring participants in the player traits with sufficient reliability, without making the survey too long. Prior to carrying out the analysis, we verified the sample adequacy. Regarding sample size, we considered literature that specifically investigated the conditions that influence the stability of the results, instead of the generic suggestions from textbooks, which usually do not consider the characteristics of each sample and each instrument. Three studies [14, 20, 40] independently concluded that good factor analysis results can be achieved with even 100–150 participants if the number of items per factor and the loading saturation (how much each item loads into their respective factor) are good. Our study included 10 items per factor (considered a good variable sampling) and the five items retained per factor had most loadings above 0.60 (considered good) or above 0.80 (very good). Thus, our sample of $N = 175$ was more than enough to produce stable results. Furthermore, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .808, meaning that the sample was large enough to perform the analysis, and Bartlett's Test of Sphericity was significant ($\chi^2{}_{1275} = 5043.0, p < .001$), indicating that the correlations between items were sufficiently large.

The responses to the Likert items are non-parametric, with several variables showing absolute values of skewness and/or kurtosis above 1.0. Therefore, we used a polychoric correlation matrix, as recommended by Muthén and Kaplan [24]. Moreover, we employed an Oblimin rotation because we expected that the components could partially overlap. In addition, we considered factor loadings greater than .36 as significant, following Field's [12] (p. 644) recommendation for a sample size of ~ 200 and $\alpha = .01$. An inspection of the screen plot showed a large drop of the eigenvalues after the fifth factor, suggesting that five factors should be retained, which was expected because the survey structure and the items were based on the five-trait model already described. The analysis was carried out using **FACTOR 10.8.02** [18]. The results are presented in Table 2.

Table 2. Factor analysis (structure matrix) of the player traits.

Items	Components 1 (T)	2 (I)	3 (G)	4 (S)	5 (A)
I1	**.724**				
I4	**.721**				
T8	**.694**				
T4	**.684**				
T5	.681				
T3	**.631**				
I5	.556				
G2	.537				
T2	.520				
T9	.508				
I3	.468				
T1	.426				
T10	.415				
I10					
T7					
I7 (R)		**-.840**			
I9 (R)		**-.686**			
I2	.480	**-.650**			
I6	.535	**-.622**			
I8 (R)		**-.613**			
G7			**.812**		
G1 (R)			**.804**		
G8			**.771**		
G6			**.566**		
G9	.437		**.563**		
G10 (R)		.507	.513		
G4 (R)		.366	.496		
G5 (R)			.438		
G3	.401		.422		
S6				**.874**	
S1				**.837**	
S4 (R)				**.819**	
S8				**.804**	
S2 (R)				**.793**	
S10				.791	
S7				.755	
S3				.747	
S9 (R)				.741	
S5				.681	
A9					**.846**
A1					**.842**
A3					**.821**
A2					**.795**
A7					**.785**
A6 (R)					.766
A5					.724
A4					.504
A8 (R)					.487
A10					.433
T6 (R)					
Eigenvalues	9.906	6.815	5.021	3.177	2.600
% of variance	19.424	13.363	9.845	6.230	5.098
Internal reliability (α) with five items by factor	.753	.843	.819	.914	.854

Notes. Extraction method: Unweighted Least Squares (ULS). Rotation method: Normalized Direct Oblimin. For improved visualization, the loadings < .36 (absolute values) are suppressed. The items marked in bold were the five items kept per factor. Items marked with (R) were reversed for scoring.
T = Aesthetic, I = Immersion, G = Goal, S = Social, A = Action.

After inspecting the results, we decided to keep five items per trait. Therefore, our final player traits survey contains 25 items. This number results in a survey with a good length, which can be quickly completed, while still keeping a good reliability: Cronbach's α for all traits with five items was $\geq .753$ (see Table 2). The retained items are marked in bold in Table 2. The five items selected per factor were those with the highest loadings, except the last item for factor 1 (aesthetic orientation): since the fifth highest loading item (T5) was semantically similar to the second and third, we decided to keep the sixth (T3) instead.

4.2 Confirmatory Factor Analysis and Test-Retest Reliability

After selecting the final five items per trait to keep, we conducted a confirmatory factor analysis (CFA) with the second half of the dataset (157 responses) using structural equation modelling (SEM) to verify the goodness of fit of the measurement model for the player traits. We carried out the analysis using the maximum likelihood method on **lavaan** [30], an open-source **R** package for SEM. The five player traits were modelled as latent variables, with the five items per trait as the observed measures. Figure 1 shows the SEM path model and the calculated coefficients.

The calculated fit statistics show that the model is adequate: Comparative Fit Index (CFI) = .927 (a $CFI \geq .90$ represents a good fit [17]); Root Mean Square Error of Approximation ($RMSEA$) = .058 (90% CI = .051, .064; $p < .05$) (a $RMSEA < .08$ represents a good fit [17]); and Standardized Root Mean Square Residual ($SRMR$) = .067 (a $SRMR < .08$ represents a good fit [17]). We did not use the chi square test because it is a poor measure of model fit for large sample sizes and models with strong correlations [22, 31]. Similarly, we did not use the Goodness of Fit Index (GFI) because its value is influenced by the sample size and degrees of freedom, thus rendering the interpretation very difficult [19, 34].

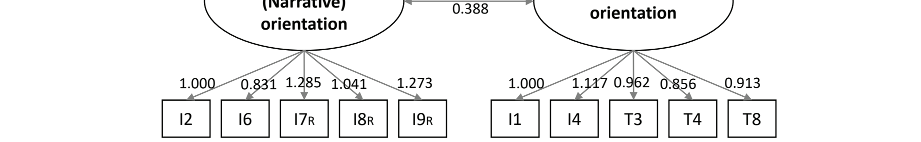

Fig. 1. Structural equation path model with calculated coefficients.

Table 3. Heterotrait-Monotrait ratio of correlations (HTMT) between the player traits.

Player Traits	**1 (T)**	**2 (I)**	**3 (G)**	**4 (S)**	**5 (A)**
1- Aesthetic orient.	–				
2- Immersion orient.	0.499	–			
3- Goal orient.	0.300	0.271	–		
4- Social orient.	0.128	0.200	0.090	–	
5- Action orient.	0.142	0.109	0.225	0.264	–

Table 4. Tentative and definitive trait names.

Factor	**Originally suggested name**		**Newly proposed name**
1	Aesthetic orientation	→	Aesthetic orientation
2	Immersion orientation	→	Narrative orientation
3	Goal orientation	→	Goal orientation
4	Social orientation	→	Social orientation
5	Action orientation	→	Challenge orientation

Furthermore, we evaluated the discriminant validity of the factors using the Heterotrait-Monotrait ratio of correlations (HTMT) [16], calculated by the **semTools** package for **R**. Values below .90 indicate good discriminant validity [16]. Therefore, the results (see Table 3) showed no problems of discriminant validity, meaning that our traits are sufficiently different from each other.

We also calculated the test-retest reliability of the 25-item scale to ensure that it leads to similar scores each time someone completes it. We calculated the player trait scores using the retained five items per trait for the 70 participants who completed the follow-up survey, then compared their follow-up with their original scores. The correlations between test and retest scores are all significant with $p < .01$ (Pearson's r, one-tailed) and the following coefficients: social orientation: $r = .906$; aesthetic orientation: $r = .763$; action orientation: $r = .813$; goal orientation: $r = .844$; and immersion orientation: $r = .768$. This demonstrates that the scale is stable, meaning that a person is likely to obtain similar scores each time they take it, provided that they still have similar preferences.

4.3 Player Traits Nomenclature

Upon completion of the analyses and inspection of the five items retained per trait, we better understood what gaming preferences are associated with each trait. Therefore, we were able to reevaluate the nomenclature originally suggested by Tondello et al. [35] and we propose two modifications (see Table 4).

While factor 2 had been tentatively named as *immersion orientation*, the retained items for this factor are all related to narrative and story, whereas other aspects of immersion did not strongly contribute to this trait. Thus, we contend that *narrative orientation* is a better name for this trait. Additionally, a closer inspection of the five retained items for factor 5 (*action orientation*) shows that they are all related to challenge and difficulty. Hence, we contend that *challenge orientation* is a better name for this trait. From this point on, we only refer to the player traits using this newly proposed nomenclature.

4.4 Correlation Between Traits and with Personality

Table 5 presents the mean scores for each player trait, as well as the bivariate correlations (Pearson's r) between them. We calculated the trait scores for each participant as a mean percentage of the values of the 7-point Likert scale. This was also how the scores were presented to participants because a percentage is generally easier to understand than a 1–7 scale. The results suggest that aesthetic orientation and narrative orientation are the strongest player traits overall. In addition, weak or strong aesthetic and narrative playing orientations seem to generally occur together, with a correlation of $r = .377$ between them. Other significant correlations were not further examined because they are weaker.

Table 5. Descriptive statistics (mean and standard deviation) for the player traits and bivariate correlations (Pearson's r) of the traits between themselves. ($N = 332$)

Player Traits	**M**	**SD**	**1 (A)**	**2 (N)**	**3 (G)**	**4 (S)**	**5 (C)**
1- Aesthetic or.	80.1%	14.8	–				
2- Narrative or.	77.7%	18.6	.377 **	–			
3- Goal or.	58.2%	19.9	.174 **	.182 **	–		
4- Social or.	51.4%	24.7	.069	-.184 **	-.049	–	
5- Challenge or.	64.8%	18.6	.093	-.033	.180 **	.236 **	–

** $p < .01$.
A= Aesthetic, N= Narrative, G= Goal, S= Social, C= Challenge

Table 6 presents the bivariate correlations between the player traits and the Big-5 personality traits [13]. Since many studies in games user research try to understand playing preferences through personality traits, it is important to determine if the player traits proposed here are sufficiently different from, and a better alternative to understanding player preferences than personality traits.

Upon inspection of Table 6, aesthetic and narrative orientations are correlated with openness to experience. It is to be expected that more open people would be more interested in aesthetic experiences, which explains these correlations. In addition, a negative correlation exists between narrative orientation and extraversion, showing that more introverted tend to enjoy games with strong narratives and stories. Next, we can see correlations of goal orientation with conscientiousness and neuroticism. This is to be expected because more conscientious people tend to be more organized and industrious; thus, they would feel more satisfaction from completing goals. On the other hand, social orientation is correlated with extraversion and agreeableness, and also negatively correlated with neuroticism. It is to be expected that more extraverted and agreeable people would be more inclined to play together with others. Finally, there is a negative

Table 6. Bivariate correlations (Pearson's r) between players traits and Big-5 personality traits, game elements, and game playing styles. ($N = 332$)

Personality Traits	**1 (A)**	**2 (N)**	**3 (G)**	**4 (S)**	**5 (C)**
1- Extraversion	-.106	-.169 **	-.033	.254 **	.060
2- Agreeableness	-.024	-.035	.086	.149 **	.067
3- Conscientiousness	-.054	-.022	.141 *	.077	.052
4- Neuroticism	.104	.004	.118 *	-.129 *	-.175 **
5- Openness	.248 **	.127 *	.055	-.082	-.062
Game Elements	**1 (A)**	**2 (N)**	**3 (G)**	**4 (S)**	**5 (C)**
1- Strategic resource mgmt.	.039	.063	.131 *	.205 **	.202 **
2- Puzzle	.163 **	.100	.180 **	-.005	.234 **
3- Artistic movement	.006	-.113 *	.037	.154 **	-.027
4- Sports and Cards	-.130 *	-.224 **	-.010	.199 **	.130 *
5- Role-playing	.479 **	.492 **	.210 **	.015	.111 *
6- Virtual Goods	.305 **	-.020	.248 **	.229 **	.086
7- Simulation	.521 **	.396 **	.133 *	.071	.033
8- Action	.311 **	.035	.040	.241 **	.403 **
Game Playing Styles	**1 (A)**	**2 (N)**	**3 (G)**	**4 (S)**	**5 (C)**
1- Multiplayer	.088	-.166 **	.041	.818 **	.263 **
2- Abstract interaction	-.045	.028	.039	.103	.145 **
3- Solo playing	.363 **	.256 **	.088	-.115 **	.238 **
4- Competitive community	.097	-.133 *	-.021	.460 **	.271 **
5- Casual play	.098	-.036	-.055	.115 *	-.173 **

* $p < .05$. ** $p < .01$.
A= Aesthetic, N= Narrative, G= Goal, S= Social, C= Challenge

correlation between challenge orientation and neuroticism. The reason for this correlation could be that difficult challenges would make more neurotic people anxious; therefore, they would probably prefer less challenging games. However, it is important to note that all these correlations are weak. Therefore, we can conclude that the player traits and personality traits are related, but they cannot be considered the same. Likely, a person's personality has some sort of influence in the way that they play games, but personality alone does not explain all the different playing preferences between people.

4.5 Correlations with Game Elements and Game Playing Styles

In this section, we show evidence that the player traits are actually related to different preferences when people play games, thus supporting the model's construct validity. We do this by analyzing the bivariate correlations of participants' player traits scores with their self-reported preferences for different game elements and game playing styles.

Regarding participants' preferences for different game elements (see Table 6), the significant correlations between aesthetic and narrative orientation with role-playing and simulation game elements are expected because these kind of games are generally focused on narrative and other aesthetic experiences. Aesthetic orientation is also correlated with virtual goods and action, showing that players likely perceive some sort of aesthetic experience when interacting with these game elements. Narrative orientation is also negatively correlated with sports and cards, which makes sense if we consider that these kinds of games usually have no story at all. Next, the correlation of goal orientation with puzzle, role-playing, and virtual goods can be explained because these kinds of elements are strongly based on setting goals for players to complete (e.g., to solve a puzzle, to enhance a character, or to acquire a specific in-game good). On the other hand, the correlations of social orientation with sports and cards, virtual goods, and action are explained because these three kinds of games have some element of player interaction, such as multiplayer modes or a virtual economy where players can exchange virtual goods. Finally, the correlation of challenge orientation with strategic resource management, puzzle, and action makes sense because these game elements pose difficult challenges for players to overcome. We did not consider the correlations with $r < .2$ relevant due to their very weak effect size. Because of a data collection error, we did not have the data to analyze the correlations with progression game elements. We suppose that participants with high goal orientation will enjoy progression game elements, but unfortunately we were not able to confirm this assumption due to the lack of data.

Considering participants' preferences for different game playing styles (see Table 6), the strong correlation between social orientation and multiplayer gaming is to be expected because several items of the social orientation trait refer to playing together. For a similar reason, a moderate correlation exists between social orientation and competitive community. Additionally, the significant correlations of aesthetic and narrative orientations with solo playing are understandable because playing alone usually gives the player more space to immerse themselves in the game's narrative and the aesthetic experience than when playing with others. Finally, challenge orientation is negatively correlated with casual playing and positively correlated with all other playing styles. This can be explained by casual games generally offering shorter and less challenging gameplay, thus they will be less appreciated by players who seek challenging experiences. Goal orientation did not show any significant correlation, meaning that it does not influence people's preferences for different playing styles.

5 Discussion

In the present work, we contribute a new, validated, 25-item survey to score people regarding their playing traits. Moreover, we present evidence that our player traits model is consistent and reliable. Furthermore, the player traits are helpful in understanding player preferences for different game elements and game playing styles, and are sufficiently different from the Big-5 personality traits.

Summarizing the results detailed in the previous section, these are the main characteristics of each player trait:

Aesthetic orientation: players who score high on this trait enjoy aesthetic experiences in games, such as exploring the world, enjoying the scenery, or appreciating the quality of the graphics, sound, and art style. On the other hand, players who score low might focus more on gameplay than the aesthetics of the game. Players who score higher on this trait are usually more open to experience, enjoy role-playing and simulations games, and enjoy playing alone.

Narrative orientation (formerly Immersion orientation): players who score high on this trait enjoy complex narratives and stories within games, whereas players who score low usually prefer games with less story elements and might skip the story or cutscenes when they feel that those get in the way of gameplay. Players who score high on this trait tend to be more open to experience and introverted, enjoy role-playing and simulation games, and enjoy playing alone.

Goal orientation: players who score high on this trait enjoy completing game goals and like to complete games 100%, explore all the options, and complete all the collections. On the other hand, players who score low might leave optional quests or achievements unfinished. Players who score higher in this trait tend to be slightly more conscientious and neurotic.

Social orientation: players who score high on this trait generally prefer to play together with others. They enjoy multiplayer games and competitive gaming communities, whereas players who score low would prefer to play alone. Players who score higher in this trait tend to be slightly more extraverted, more agreeable, and less neurotic.

Challenge orientation (formerly Action orientation): players who score high on this trait generally prefer difficult games and hard challenges. On the other hand, players who score low prefer easier or casual games. Players who are more neurotic tend to score lower in this trait. Players who score high on this trait tend to enjoy all game playing styles, except casual games.

There is a partial correlation between aesthetic and immersion orientations (see Table 5). This is why items I2 and I6 load significantly in both factors in Table 2. Therefore, it is important to understand the differences between them. Players with high aesthetic orientation might enjoy narratives as a type of aesthetic experience, but they will still enjoy a game with a simpler story if there are other aesthetic elements to appreciate. On the other hand, players with high immersion orientation will not enjoy games without elaborate stories or narratives. Additionally, players with low aesthetic orientation are not likely to feel that the story prevents their enjoyment of the gameplay, whereas players with low immersion orientation will probably feel that complex stories get in the way of gameplay and are more likely to skip narratives and cutscenes.

5.1 Applications of the Model

There are many ways to use the player traits model in game design, marketing, and research. Game designers can use it by adding our 25-items to their intake survey for potential playtesters, which allows more focused playtesting.

For example, when testing Destiny [7], a multiplayer first-person science-fiction shooter, it is important to test players with high scores in social, aesthetic, and challenge orientations, as they are most likely to be satisfied by the gameplay.

Our survey can also be used earlier in production by giving designers more information on the preferences of their audience. For example, a game studio might want to explore options for a new game. By asking players to fill out the player traits survey, they can learn what are their most prominent traits. Then, they can look at the list of game elements and game playing styles correlated to these traits to seek ideas that will satisfy their players. Or, if the trait scores for a player are available during gameplay, some mechanics may be dynamically activated or deactivated, thus providing a personalized gaming experience.

Those in marketing departments can also use our model by applying our items to their existing surveys, allowing them to target players whose orientations will be best served by the elements of their game. For example, it would be important to target those with narrative, goal, and challenge orientations when marketing Far Cry 5 [37] because it contains game elements that would be appealing to players with those traits, such as branching storyline and side quests.

These potential applications would not be possible with any of the existing models described in the Related Work, either because a measurement instrument is not available for them, or because the existing instrument is not reliable.

5.2 Comparison with Existing Models

Our work presents the first publicly available model of player preferences based on traits instead of categorical types, and with a validated measurement scale. Nevertheless, we provide a specific comparison with some of the existing works.

Since the development of the player traits was inspired by the BrainHex [26], there is a correspondence between them: social orientation with BrainHex's socialiser archetype; aesthetic orientation with seeker; challenge orientation with conqueror and daredevil; goal orientation with mastermind, achiever, and survivor; but narrative orientation is a new trait. However, our player traits model uses a well accepted approach inspired by trait theories instead of types and differently from the BrainHex, our measurement survey has demonstrated validity.

Regarding Bartle's typology [1, 2], social orientation would correspond to Bartle's socialiser; goal orientation would correspond to achiever; and aesthetic orientation would correspond to explorer; but there is no player trait which corresponds directly to killer. However, these are only theoretical assumptions because we did not conduct any empirical comparison of these models.

Comparing our player traits model with Yee's gamer motivation profile [42], social orientation is present in both models; aesthetic orientation corresponds to creativity; challenge orientation to mastery; goal orientation to achievement; and narrative orientation to immersion. But there is no player trait corresponding to action motivations. Although Tondello et al. [35] had initially suggested an action orientation trait, in our study the challenge-oriented motivations were more pronounced than action-oriented ones. Future studies could explore if action orientation should be a sixth player trait, which our work did not discern.

Moreover, social orientation is similar to the sociability concept from Hamari and Tuunanen's [15] meta-synthesis of player types; aesthetic orientation to exploration; goal orientation to achievement; and narrative orientation to immersion. Challenge orientation may lead some players to the domination behaviours from their meta-review, but these concepts are not exactly the same. Future work could investigate the similarities and differences between these two constructs to better understand what drives players in each case.

Finally, although we employed SDT to help explain the theoretical background of the player traits, SDT alone cannot be used to understand player preferences. SDT-based scales such as the Player Experience of Need Satisfaction [33] and the inventory of intrinsic motivations to gameplay [38] can only explain the general motivations that lead people to play and enjoy games, but they say nothing about different player preferences.

5.3 Limitations and Future Work

Although we present considerable evidence of the validity of the five-factor player traits model and the 25-item measurement scale, our study has a few limitations. First, all data came from self-reported answers. Therefore, future studies should confirm if players' self-reported preferences correspond to their actual behaviour when playing games. In addition, although our dataset was large enough to carry out all the statistical analyses, further validation of the model with more participants would contribute to increasing confidence in it. Moreover, the personality traits scale that we used (BFI-10) is short and less accurate than longer ones. This can be a reason for low correlations detected with player traits. Future studies could employ longer personality scales for a new analysis of these correlations. Finally, our study validated the existence of the five player traits. However, these traits only partially explained participants' gaming preferences. Thus, we cannot determine if these are the only traits that affect gaming preferences, or if more traits should be added to the model in the future.

6 Conclusion

This research introduces a new player preferences model that solves the issues identified in previous work. The player traits model had been initially proposed by Tondello et al. [35] based on previous player typologies, in particular the BrainHex scale. Now, our work introduces a validated measurement scale and provides empirical evidence of the model's construct and discriminant validity. It is the first model based on player traits instead of types, which better captures the full range of individual preferences. Its use to the game design, marketing, and research communities is abundantly evident as it can inform and analyze the design of games, marketing campaigns, and user research studies.

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References

1. Bartle, R.: Hearts, Clubs, Diamonds, Spades: Players who suit MUDs. Journal of MUD Research **1**(1) (1996)
2. Bartle, R.: Virtual Worlds: Why People Play. Massively Multiplayer Game Development **2**(1) (2005)
3. Bateman, C., Boon, R.: 21st Century Game Design (Game Development Series). Charles River Media (2006)
4. Bateman, C., Lowenhaupt, R., Nacke, L.E.: Player Typology in Theory and Practice. Proceedings of DiGRA 2011 (2011)
5. Bateman, C., Nacke, L.E.: The Neurobiology of Play. In: Proceedings of Futureplay 2010. pp. 1–8. ACM, Vancouver, BC, Canada (2010). https://doi.org/10.1145/1920778.1920780
6. Birk, M.V., Toker, D., Mandryk, R.L., Conati, C.: Modeling Motivation in a Social Network Game Using Player-Centric Traits and Personality Traits. In: Proceedings of User Modeling, Adaptation and Personalization. pp. 18–30. Springer (2015). https://doi.org/10.1007/978-3-319-20267-9_2
7. Bungie: Destiny. Game [XBOX 360] (September 2014), Activision, Santa Monica, CA
8. Busch, M., Mattheiss, E., Orji, R., Fröhlich, P., Lankes, M., Tscheligi, M.: Player Type Models – Towards Empirical Validation. In: Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems. ACM (2016). https://doi.org/10.1145/2851581.2892399
9. Caillois, R.: Man, Play, and Games. University of Illinois Press (1961)
10. Costa Jr, P.T., McCrae, R.R.: Trait theories of personality. In: Barone, D.F., Hersen, M., Van Hasselt, V.B. (eds.) Advanced Personality, pp. 103–121. Springer (1998). https://doi.org/10.1007/978-1-4419-8580-4_5
11. Deci, E.L., Ryan, R.M.: Intrinsic Motivation and Self-Determination in Human Behavior. Plenum, New York and London (1985)
12. Field, A.: Discovering Statistics Using SPSS. Sage Publications, London, UK, 3rd edn. (2009)
13. Goldberg, L.R.: The structure of phenotypic personality traits. American Psychologist **48**(1), 26–34 (1993). https://doi.org/10.1037/0003-066X.48.1.26
14. Guadagnoli, E., Velicer, W.F.: Relation of sample size to the stability of component patterns. Psychological Bulletin **103**(2), 265–275 (1988). https://doi.org/10.1037/0033-2909.103.2.265
15. Hamari, J., Tuunanen, J.: Player types: A meta-synthesis. Transactions of the Digital Games Research **1**(2) (2014), http://todigra.org/index.php/todigra/article/view/13
16. Henseler, J., Ringle, C.M., Sarstedt, M.: A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science **43**(1), 115–135 (2015). https://doi.org/10.1007/s11747-014-0403-8
17. Kline, R.B.: Principles and Practice of Structural Equation Modeling. The Guilford Press, 3rd edn. (2010)
18. Lorenzo-Seva, U., Ferrando, P.: FACTOR 9.2: A Comprehensive Program for Fitting Exploratory and Semiconfirmatory Factor Analysis and IRT Models. Applied Psychological Measurement **37**(6), 497–498 (2013)
19. MacCallum, R.C., Hong, S.: Power Analysis in Covariance Structure Modeling Using GFI and AGFI. Multivariate Behavioral Research **32**(2), 193–210 (1997). https://doi.org/10.1207/s15327906mbr3202_5

20. MacCallum, R.C., Widaman, K.F., Zhang, S., Hong, S.: Sample Size in Factor Analysis. Psychological Methods **4**(1), 84–99 (1999)
21. Malone, T.W.: Toward a Theory of Intrinsically Motivating Instruction. Cognitive Science **4**, 333–369 (1981)
22. Matsunaga, M.: How to factor-analyze your data right: do's, don'ts, and how-to's. International Journal of Psychological Research **3**(1), 97–110 (2010). https://doi.org/10.21500/20112084.854
23. McCrae, R.R., Costa, P.T.: Reinterpreting the Myers-Briggs type indicator from the perspective of the five-factor model of personality. Journal of Personality **57**(1), 17–40 (1989). https://doi.org/10.1111/j.1467-6494.1989.tb00759.x
24. Muthén, B., Kaplan, D.: A comparison of some methodologies for the factor analysis of non-normal Likert variables. British Journal of Mathematical and Statistical Psychology **38**, 171–189 (1985)
25. Myers, I.B.: The Myers-Briggs Type Indicator. Consulting Psychologists Press, Palo Alto, CA (1962)
26. Nacke, L.E., Bateman, C., Mandryk, R.L.: BrainHex: A Neurobiological Gamer Typology Survey. Entertainment Computing **5**(1), 55–62 (2014). https://doi.org/10.1016/j.entcom.2013.06.002
27. Newman, K.: The Case for the Narrative Brain. In: Proceedings of the Second Australasian Conference on Interactive Entertainment. pp. 145–149. Creativity & Cognition Studios Press (2005)
28. Orji, R., Mandryk, R.L., Vassileva, J., Gerling, K.M.: Tailoring persuasive health games to gamer type. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13. pp. 2467–2476 (2013). https://doi.org/10.1145/2470654.2481341
29. Rammstedt, B., John, O.P.: Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. Journal of Research in Personality **41**(1), 203–212 (2007). https://doi.org/10.1016/j.jrp.2006.02.001
30. Rosseel, Y.: lavaan: An r package for structural equation modeling. Journal of Statistical Software, Articles **48**(2), 1–36 (2012). https://doi.org/10.18637/jss.v048.i02
31. Russell, D.W.: In Search of Underlying Dimensions: The Use (and Abuse) of Factor Analysis in Personality and Social Psychology Bulletin. Personality and Social Psychology Bulletin **28**(12), 1629–1646 (2002). https://doi.org/10.1177/014616702237645
32. Ryan, R.M., Deci, E.L.: Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. The American Psychologist **55**(1), 68–78 (2000). https://doi.org/10.1037/0003-066X.55.1.68
33. Ryan, R.M., Rigby, C.S., Przybylski, A.: The motivational pull of video games: A self-determination theory approach. Motivation and Emotion **30**(4), 347–363 (2006). https://doi.org/10.1007/s11031-006-9051-8
34. Sharma, S., Mukherjee, S., Kumar, A., Dillon, W.R.: A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. Journal of Business Research **58**(7), 935–943 (2005). https://doi.org/10.1016/j.jbusres.2003.10.007
35. Tondello, G.F., Valtchanov, D., Reetz, A., Wehbe, R.R., Orji, R., Nacke, L.E.: Towards a Trait Model of Video Game Preferences. International Journal of Human-Computer Interaction **34**, 732–748 (2018). https://doi.org/10.1080/10447318.2018.1461765

36. Tondello, G.F., Wehbe, R.R., Orji, R., Ribeiro, G., Nacke, L.E.: A Framework and Taxonomy of Videogame Playing Preferences. In: Proceedings of the 2017 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '17. pp. 329–340. ACM, Amsterdam, Netherlands (2017). https://doi.org/10.1145/3116595.3116629
37. Ubisoft Montreal, Ubisoft Toronto: Far Cry 5. Game [Microsoft Windows] (March 2018), Ubisoft, Montreuil, France
38. Vahlo, J., Hamari, J.: Five-Factor Inventory of Intrinsic Motivations to Gameplay (IMG). In: Proceedings of the 52$^{\text{nd}}$ Hawaii International Conference on System Sciences (HICSS). pp. 2476–2485. University of Hawai'i at Manoa (2019), http://hdl.handle.net/10125/59686
39. Vahlo, J., Kaakinen, J.K., Holm, S.K., Koponen, A.: Digital Game Dynamics Preferences and Player Types. Journal of Computer-Mediated Communication **22**(2), 88–103 (2017). https://doi.org/10.1111/jcc4.12181
40. Velicer, W.F., Fava, J.L.: Affects of variable and subject sampling on factor pattern recovery. Psychological Methods **3**(2), 231–251 (1998). https://doi.org/10.1037/1082-989X.3.2.231
41. Yee, N.: Motivations for Play in Online Games. CyberPsychology & Behavior **9**(6), 772–775 (2006). https://doi.org/10.1089/cpb.2006.9.772
42. Yee, N.: Gamer Motivation Model Overview and Descriptions. Quantic Foundry (December 2015), http://quanticfoundry.com/2015/12/15/handy-reference/
43. Yee, N.: Gaming Motivations Align with Personality Traits. Quantic Foundry (January 2016), http://quanticfoundry.com/2016/01/05/personality-correlates/
44. Yee, N., Ducheneaut, N., Nelson, L.: Online Gaming Motivations Scale: Development and Validation. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '12. pp. 2803–2806. ACM (2012). https://doi.org/10.1145/2207676.2208681