Player Characteristics and Video Game Preferences

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ABSTRACT
The Games User Research literature has advanced considerably on understanding why people play games and what different types of games or mechanics they prefer. However, what has been less studied is how models of player preferences explain their game choices. In this study, we address this question by combining and analyzing two datasets ($N = 188$ and $N = 332$) containing data about the games that participants enjoy, their player trait scores, and their preferred game elements and playing styles. The results provide evidence that these scores can significantly explain participants' preferences for different games. Additionally, we provide information about the characteristics of players who enjoy each game.

CCS Concepts
•**Human-centered computing** → **User models; Empirical studies in HCI;** •**Applied computing** → **Computer games;** •**Information systems** → *Massively multiplayer online games;* •**Software and its engineering** → *Interactive games;*

Author Keywords
Video games; games user research; player traits; player preferences; game elements; personalization.

INTRODUCTION
Understanding why people play games and what different types of games or mechanics they prefer is a major interest in the Games User Research (GUR) community. This knowledge is important because it facilitates player-centric design and helps designers build games better tailored to what their audience wants [72, 74, 78]. In addition, marketing practices of segmentation and differentiation are increasingly common as a part of game design with the goal of better selling virtual goods to specific players [42]. But this is only possible if the game studios have a good model of player preferences to segment their audience. Knowledge about player preferences can also be used to design serious games that are more effective in helping players achieve their instrumental goals [62, 63].

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In the recent years, research on player motivations and preferences has advanced considerably, with publications that address why people play games [41] and consider them intrinsically motivating [65, 68, 77], what player traits [72, 73], motivations [86, 87, 92], or demographic characteristics [15, 39, 73, 85] explain preferences for different gaming styles, and how player preferences for different game elements, dynamics, or playing styles can be classified [74, 78]. However, what has been less studied is how different individual characteristics explain players' choices of different games. Tondello et al. [73] studied the relationship between game choices, player traits, gender, and attitude towards story in games. Player traits are continuous scores representing individual player preferences such as goal orientation, social orientation, and aesthetic orientation. However, Tondello et al. used a preliminary version of the traits model, which has been recently replaced by a new, validated version [72]. Similarly, Quantic Foundry [89] studied the relationship between game choices, gaming motivations, and demographic characteristics, but their data is proprietary and is not publicly available.

To address the need for a better understanding of the games preferred by players with different characteristics, we studied the datasets previously collected by Tondello et al. [72, 74]. While the data have already been studied to develop a framework and taxonomy of game playing preferences [74] and a player traits model and scale [72], participants also listed games that exemplify the kind of games that they like, but this information has not been studied yet. Now, we look at their responses to answer the following research questions:

RQ1: How do player trait scores influence the player's choice of games?

RQ2: How do player's preferred game elements and game playing styles influence their choice of games?

RQ3: How do player's gender and age influence their choice of games?

Answering these questions is important because they can help understand the characteristics of the player base of each game. The set of games we analyzed is representative of the most successful commercial video game franchises, such as *The Legend of Zelda*, *The Elder Scrolls*, and *Pokémon*. But although these games are frequently studied, copied, or used as inspiration for new games, it is not always clear what types of players enjoy each game because the companies behind them may not publish their player demographics. By better understanding the characteristics and preferences of players

that enjoy each game, we provide insights about them, which can serve as references to target the design of games inspired by these incredibly successful franchises.

The player characteristics chosen as research questions are useful to understand player preferences, based on the evidence available in the literature. Accordingly, there is evidence that the psychological traits of the players [42, 59, 64, 73] (RQ1), their preferred game elements or mechanics [74, 78] (RQ2), and their age [15, 90] and gender [85, 88, 91] (RQ3) are related to players' choice of games or genres. Therefore, by further studying these specific player characteristics, we contribute with empirical evidence that they are significantly related to different choices of games.

RELATED WORK

The research on the relationship between games and players can be divided in two broad categories: (1) why people play games and find them intrinsically motivating, and (2) what different types of games or gameplay each person prefers. The later category can further be subdivided into two because we can classify the characteristics of people (for example, player types or traits) or the characteristics of games (for example, grouping game elements according to player preferences).

The literature on general motivations to play games can help understand what makes games enjoyable in general. For example, scholars have investigated why people play games [41], why games are fun [50, 51, 84], and how game play satisfies psychological needs for autonomy, competence, and relatedness [65, 68, 77]. Although there is an extensive literature on this line of investigation, it is not aimed at explaining differences between players. For example, why do some players satisfy their psychological needs by taking on the role of a fictional character and immersing themselves into a simulated open virtual world, whereas others prefer to test their skills by jumping between platforms, shooting enemies, or playing e-sports, or others prefer to make complex strategic decisions to balance resources? Thus, the need to understand these differences led to another line of studies, aimed at understanding the characteristics of players.

Classifications of the Characteristics of Players

Throughout the years, many attempts have been made with the goal of understanding the differences between player preferences and behaviours (see [42] for a review). One of the earliest (but still very popular) studies is Bartle's [5]. He studied what players enjoyed on Multi-User Dungeons (MUDs) and developed a model based on two axes that represent players' interaction with the virtual world or with other players. In Bartle's typology, Achievers seek to earn points or other rewards in the game, Socialisers focus on social interactions within the game and with other players, Explorers enjoy discovering and learning the game world, and Killers focus on competitive game play and defeating other players. Bartle later expanded the model with a third dimension: whether the players' actions are implicit or explicit [6].

While Bartle's model was only based on one type of game, it inspired two important research projects, which progressively studied player preferences throughout many years to develop more general models. One of these projects is the work of Yee and colleagues [86, 92]. Based on a factor analysis, they identified three main components of player motivation: achievement, social, and immersion. However, their analyses were also based on only one game genre (Massively Multiplayer Online Role-Playing Games - MMORPGs). But more recently, they expanded on their previous work through their company Quantic Foundry, ultimately leading to an analysis with over 140,000 participants of all game genres and the development of the Gamer Motivation Profile [87]. In this model, 12 dimensions of player motivations 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).

Another large project developed the BrainHex [58, 59], based on a series of demographic game design studies and neurobiological research [7, 8]. The BrainHex introduces 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). However, two independent studies [24, 73] found several issues related to its psychometric properties (factor validity, stability, and consistency). Building upon this work, Tondello et al. [72] then developed a Player Traits model to replace the BrainHex and address its issues, which we review in detail on the next subsection.

Vahlo et al. [78, 79] also recently developed a model of player preferences, based on a factor analysis of a large data sample about players' preferred gameplay activities. First, they classified gameplay activities into five groups: Management, Aggression, Exploration, Coordination, and Caretaking. Next, they performed a cluster analysis to group players with similar preference profiles, identifying six player types: Mercenary (motivated by aggression), Adventurer (motivated by exploration), Explorer (motivated by coordination and exploration), Companion (motivated by caretaking), Supervisor (motivated by management), and Acrobat (motivated by coordination).

Player Traits Model

Some of the initial player preferences model, such as Bartle's work and the BrainHex, tried to classify players into distinct types. However, player type models rarely work in practice because people actually have several overlapping motivations. Rarely is someone motivated by a single factor [72]. Similarly, theories that try to classify individuals into a single type have been criticized as inadequate in personality research, giving ground to trait theories [38, 54]. Trait theories interpret an individual as a sum of different characteristics rather than classifying them in separate categories. Therefore, trait theories have been suggested to also be a better approach to classify player motivations and behaviours in games [42, 72, 73].

The Player Traits model [72], which is inspired by the trait theories of personality, posits that each player is characterized by a set of five different scores, each score measuring where their preferences sit on a continuum for each player trait. The five player traits are:

Aesthetic orientation: Players who score high on this trait enjoy the aesthetic experiences in games, siuch as exploring the world, observing 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 the gameplay than the aesthetics of the game.

Narrative orientation: Players who score high on this trait enjoy complex stories or narratives within games, whereas players who score low usually prefer games with less story and might skip the cutscenes when they get in the way of gameplay.

Goal orientation: Players who score high on this trait enjoy completing game goals, quests, or tasks, 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 unfinished and are usually more relaxed if they do not complete a game 100%.

Social orientation: Players who score high on this trait generally prefer to play together with others online or in the same space and enjoy multiplayer games and competitive gaming communities. On the other hand, players who score low would usually prefer to play alone.

Challenge orientation: Players who score high on this trait generally prefer difficult games, hard challenges, and fast-paced gameplay, whereas players who score low might prefer easier or casual games.

Classifications of the Characteristics of Games

While the research reviewed on the previous subsection focus on which characteristics of players makes them prefer different types of games, other studies classified the elements and playing styles commonly found in games according to how they are enjoyed by similar players. Thus, Tondello et al. [74] and Vahlo et al. [78] developed frameworks and taxonomies of game elements, dynamics, and playing styles by player preferences. In this study, we will compare participants' choice of games with their scored preferences for different game elements and playing styles from Tondello et al.'s framework to better understand what types of gameplay people enjoy in each game.

The groups of game elements in the framework are [74]:

1. **Strategic resource management**, also including construction and strategic gameplay.
2. **Puzzle,** including diverse types of puzzles.
3. **Artistic movement**, such as music play, painting, or body movement.
4. **Sports and cards**, also including gambling.
5. **Role-playing**, such as fantasy, science fiction, and avatars.
6. **Virtual goods**, including acquisition, collection, and use of virtual goods or resources.
7. **Simulation** of scenarios inspired by real life.
8. **Action**, including exciting and fast-paced gameplay.
9. **Progression** towards accumulating power or learning.

And the groups of game playing styles are [74]:

1. **Multiplayer**, which can be collaborative or competitive.
2. **Abstract interaction,** in which the player feels less directly immersed in the game, usually playing from an isometric or a top-down view.
3. **Solo play**, in which the player might be more directly immersed in the game, by playing from a first- or third-person view and freely moving around the game world.
4. **Competitive community,** such as streaming, competing in e-sports, or co-located play.
5. **Casual play** in short sections, usually on a mobile device.

Relationships Between Player Preferences and Games

Tondello et al. [73] conducted a comprehensive study about the characteristics of players who said they enjoy 26 different games. Their research employed a large dataset and provided evidence that the participants' choice of games was related to their player trait scores, gender, and attitude toward stories in games. The games or game franchises that they analyzed were: *Baldur's Gate* [12], *Battlefield* [27], *BioShock* [2], *Call of Duty* [44], *Civilization* [55], *Counter-Strike* [82], *Deus Ex* [47], *Diablo* [21], *Elder Scrolls* [11], *Fallout* [46], *Final Fantasy* [70], *Grand Theft Auto* [28], *Half-Life* [80], *Halo* [22], *Left 4 Dead* [75], *Mass Effect* [13], *Metal Gear* [49], *Pokémon* [32], *Portal* [83], *StarCraft* [17], *Super Mario* [61], *Super Smash Bros.* [40], *Team Fortress* [81], *Warcraft* [16], *World of Warcraft* [18], and *Zelda* [60]. However, they employed a preliminary version of the player traits model, which only contained three traits (action, aesthetic, and goal orientations) and was based on the BrainHex questionnaire instead of a specific one. Therefore, in the current study, we provide additional evidence of the relationship between players' choice of games and their player trait scores, but now using a new and validated player traits scale [72] and a new list of games.

Additionally, a few studies investigated player preferences toward specific games or genres. Ducheneaut et al. [29] provided insights on what players enjoy in *World of Warcraft*. Jansz and Tanis [48] showed that first-person shooter players are highly motivated by challenges, competition, and social motivations. Frostling-Henningsson [35] found that social reasons represented participants' main motivation to play *Counter-Strike* and *World of Warcraft*. Williams et al. [85] found that male *EverQuest II* [69] players were more motivated by achievement whereas women were slightly more motivated by social interactions. Our work is more general than these studies because we are considering several games of different genres.

Vahlo et al. [79] also conducted a broad study of game preferences based on player type, gender, and age. However, they asked participants about what game genres they play, instead of game titles. They found out that:

Mercenaries are usually younger men who play action, racing, and strategy games.

Adventurers usually play role-playing and action-adventure games.

Explorers are usually women of higher age who play sports, party, and platformer games.

Supervisors usually play simulation and strategy games.

Acrobats are usually young and play sports and party games.

METHODS

In this work, we revisit the two datasets[1] previously collected by Tondello et al. [72, 74], specifically focusing on participants' answers to the question "Please name up to three games that exemplify the type of games you like". Because both datasets contained information about participants' preferred games, game elements, and game playing styles, as well as their gender and age, we combined them for all the analyses. The only exceptions are the analyses conducted to investigate the relationship between player traits and preferred games (RQ1): we only used the newer dataset [72] in this case because the older one [74] did not contain player traits data. Table1 summarizes the information about each dataset.

Dataset origin	[74]	[72]
Year of data collection	2017	2018
Participants (N)	188	332
Collected data		
Demographic data	Yes	Yes
Game choices	Yes	Yes
Preferred game elements and playing styles	Yes	Yes
Player traits	No	Yes
Usage in this study		
RQ1 (player traits)	No	Yes
RQ2 (game elements and playing styles)	Yes	Yes
RQ3 (gender and age)	Yes	Yes

Table 1. Summary of the datasets used in this study.

Participants

The first dataset [74] was collected online in 2017. Participants were required to be at least 15 years old and were recruited via email lists, social networks and online gaming forums. They were offered an opportunity to enter a draw to win one of two $ 50 prizes. After cleaning, the dataset contained 188 responses (124 men, 53 women, 4 transgender, 3 non-binary, and 4 did not inform their gender). Participants' ages ranged from 15 to 71 ($M = 26.7$, $SD = 9.7$). Participants were distributed geographically as follows: 60.6% from North America, 25.5% from Europe, 5.3% from South America, 4.8% from Oceania, 2.7% from Asia, and 1.1% from Africa.

The second dataset [72] was collected online in 2018. Participants were required to be 15 years or older and were recruited through social media and mailing lists. They were offered the possibility to enter a draw for one of two $ 50 international gift cards. After cleaning, the 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%). 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%) play less than one hour per week.

[1] Available online at: https://osf.io/au863/

Game Names: Cleaning and Selection

Participants listed up to three games that exemplify the type of game that they enjoy using a free-entry text field. Therefore, a cleaning procedure was necessary to correct problems such as spelling mistakes (e.g., "Assasin Creed" instead of "Assassin's Creed"), abbreviations (e.g., "GTA" instead of "Grand Theft Auto"), and name variations of the same game (e.g., "Skyrim" and "The Elder Scrolls: Skyrim").

Additionally, we were interested in grouping different games in a series or franchise to be analyzed together. This is similar to what Tondello et al. [73] previously did when they studied the relationship between player traits and games. The reason for this procedure is that games in the same series or franchise usually share common characteristics and appeal to the same player base. Often, players who greatly enjoy a game in a franchise are more likely to try other games in the same franchise. Thus, grouping all games of a franchise or series allowed us to use a larger participant sample to help us explain the characteristics of said franchise or series. After this additional step, the names of all games in the same franchise or series were modified to a common name. For example, "Final Fantasy 7", "Final Fantasy IX", and "Final Fantasy Tactics" were all grouped into the general label "Final Fantasy". These game name cleaning and grouping procedures were carried out manually by the first author.

After cleaning, the combined dataset contained 467 unique names of games or game series, from which 176 names were mentioned two or more times. However, analyzing 176 different games is not only unpractical, but also limits the statistical power of any analysis conducted on games with too few mentions. Therefore, we decided to only analyze the games that were mentioned at least 10 or more times by participants. We chose this number after manually inspecting the frequency distribution of games in the sample. This was the number that better seemed to include a good variety of games while offering a large enough sample for each game to enable statistical analyses. After discarding the games with less than 10 mentions, our final game list contained 37 unique names of games or game series, which correspond to 7.9% of the unique game names in the full dataset. However, these 37 games accounted for 743 out of the total 1520 game mentions in the dataset (49%). Therefore, we still retained about half the total game mentions from our datasets, while reducing the number of unique games to a manageable quantity. Table 2 lists all the games or game series considered in this study.

We also considered grouping games that were often chosen by the same participants to simplify data anlysis and results. A similar procedure was also previously carried out by Tondello et al. [73]. Therefore, we tried to use principal component analysis and hierarchical clustering to group games that often appeared together. However, the procedures did not provide good results, possibly because there were not enough data to adequately cluster games. We did not want to manually cluster games a priori because we wanted to investigate if even games that appear similar (e.g., they are classified with the same genre) may appeal to players with different characteristics. Therefore, we decided to leave the games ungrouped.

Games	Mentions from [74]	Mentions from [72]	Total
Assassin's Creed [76]	7	15	22
Borderlands [37]	5	7	12
Call of Duty [44]	5	8	13
Civilization [55]	11	19	30
Counter-Strike [82]	6	13	19
Dark Souls [34]	14	16	30
Defense of the Ancients [43]	2	13	15
Dragon Age [14]	5	10	15
Fallout [46]	14	19	33
FIFA [30]	2	9	11
Final Fantasy [70]	10	19	29
Fire Emblem [45]	2	9	11
Fortnite [31]	-	10	10
Grand Theft Auto (GTA) [28]	8	7	15
Halo [22]	5	5	10
Hearthstone [19]	3	9	12
Kingdom Hearts [71]	3	7	10
League of Legends (LoL) [36]	7	16	23
Mass Effect [13]	11	12	23
Metal Gear [49]	8	5	13
Minecraft [56]	10	14	24
Monster Hunter [1]	-	11	11
Overwatch [20]	16	17	33
Persona [3]	1	11	12
Pokémon [32]	19	26	45
Portal [83]	9	5	14
Rainbow Six [67]	2	12	14
Rocket League [66]	3	9	12
StarCraft [17]	4	6	10
Stardew Valley [4]	3	19	22
Super Mario [61]	5	12	17
The Elder Scrolls [11]	24	31	55
The Legend of Zelda [60]	18	31	49
The Sims [53]	6	8	14
The Witcher [25]	7	14	21
World of Warcraft [18]	8	16	24
X-COM [57]	4	6	10
Total mentions in this study	**272**	**471**	**743**
Other 430 games	266	511	777
Total mentions in the datasets	538	982	1520

Note. For game series, the citation refers to the first game in the series.

Table 2. Game mentions for the most common games in the datasets.

Hypotheses and Analyses

To answer **RQ1** (How do player trait scores influence the player's choice of games?), we tested if there is a significant relationship between the games mentioned by each participant and their player trait scores. Because player traits are supposed to describe the different experiences that players seek in games, it is logical to suppose that certain games would be preferred by players with high or low scores in specific traits.

Similarly, to answer **RQ2** (How do player's preferred game elements and game playing styles influence their choice of games?), we tested if there is a significant relationship between the participants' scores of their preferences for different groups of game elements and playing styles with the games that they mentioned. Although game elements and playing styles are characteristics of games, we asked how much each participant enjoys them. These preference scores are thus characteristics of players. Therefore, it is logical to think that having distinct preferred elements and playing styles would lead players to choose different games, which include at least some of the elements that they like.

Finally, to answer **RQ3** (How do player's gender and age influence their choice of games?), we tested if there is a significant relationship between participants' gender and age with the game names that they mentioned. Since previous research has already shown that gender and age do significantly influence players preferences for different games [73, 88, 90] or game elements and playing styles [74, 85], we can reasonably expect that they will also influence game choices.

Therefore, our hypotheses were:

H1: There is a significant relationship between the participant's player trait scores and the names of the games they mentioned.

H2: There is a significant relationship between the participant's scores of their game elements preferences and the names of the games they mentioned.

H3: There is a significant relationship between the participant's scores of their game playing styles preferences and the names of the games they mentioned.

H4: There is a significant relationship between the participant's gender and the names of the games they mentioned.

H5: There is a significant relationship between the participant's age and the names of the games they mentioned.

The game name is a categorical variable, which we can use to group game mentions. Thus, to test **H1**–**H3**, we needed to test if the scores of the player traits, game elements, and game playing styles were significantly different per group. This required a multivariate analysis method because each one of these constructs is represented by more than one score. However, it was not possible to use a multivariate analysis of variance (MANOVA) because our data violated the assumptions of normality (verified with the Kolmogorov-Smirnov test) and homogeneity of variances (verified with Levene's test). Therefore, we used the **npmv** package (Nonparametric Comparison of Multivariate Samples, v. 2.4.0; [23]) for the statistical software **R** (v. 3.5.2, 2018), which uses rank-based approaches to test the overall null hypothesis (see [9, 10] for the underlying theory). The package calculates four different test statistics, which all consistently led to the same results in our tests. Thus, we chose to report only the Wilks' Lambda (λ) type test statistics [52] because it is the default one to use according to the package's manual [23]. After verifying the overall significance of each relationship, we followed up with one-way Kruskal-Wallis (KW) tests on SPSS (v. 23, IBM, 2015) to find out which individual types of scores were significant. Additionally, we calculated the effect size η^2 from the KW test statistic H (see [26, 33]) and produced charts to easily compare the median scores per game.

For **H4**, the test consists on a comparison between two categorical variables (gender and game names). Therefore, we used Pearson's chi-square (χ^2) test to calculate the statistical significance and the odds of players of each gender selecting specific games, and calculated Cramer's V to estimate the effect size. Finally, we tested **H5** using the KW test to calculate the significance of the age difference between game name mentions and calculated the effect size η^2 from the KW test statistic H. We also used SPSS (v. 23) for these tests.

RESULTS

This section presents the results of the statistical analyses for each one of the hypotheses.

Relationship Between Games and Player Traits

As mentioned in the previous section, we used only the data from the second dataset to analyze the relationship between player traits and games because the other dataset did not contain player trait data. Therefore, out of the 37 games, we could only analyze the 23 that were mentioned 10 or more times in that dataset alone (games with mentions ≥ 10 on the third column of Table 2), which resulted in a total of $N = 376$ game mentions. The nonparametric comparison of multivariate samples showed an overall significant difference in the player trait scores per game: $\lambda_{(110.000,1714.532)} = 2.805; p < .001$, which supports hypothesis **H1**.

Table 3 shows the results of the Kruskal-Wallis tests to determine which player traits contributed more to the overall differences. The scores across games were significantly different for all traits except goal orientation. The larger effect was observed for social orientation ($\eta^2 = .218$), whereas narrative ($\eta^2 = .134$) and challenge orientation ($\eta^2 = .106$) showed medium-large effects and aesthetic orientation (η^2 = .077) showed a medium effect. Figure 1 further details these effects by showing the percentiles where the participants that mentioned each game fall in relation to the whole sample.

	Aest.	Nar.	Goal	Soc.	Cha.
Median	83.33	83.33	56.67	53.33	66.67
Mean	80.12	77.71	58.20	51.36	64.84
Std. Dev.	14.77	18.56	19.94	24.74	18.57
H (KW)	48.307	68.612	26.634	98.234	58.384
p	.001	< .001	.236	< .001	< .001
η^2	.077	.134	.016	.218	.106

Note. N = 376; df (KW) = 22.
Aest. = Aesthetic orientation; Nar. = Narrative orientation;
Goal = Goal orientation; Soc. = Social orientation;
Cha. = Challenge orientation.

Table 3. Kruskal-Wallis tests between Player Traits and Games.

Relationship Between Games and Game Elements

The nonparametric comparison of multivariate samples showed an overall significant difference in the game elements scores per game: $\lambda_{(288.000,5486.154)} = 2.325; p < .001$ (for the combined dataset with $N = 743$ game mentions), which supports hypothesis **H2**.

Table 4 shows the results of the Kruskal-Wallis tests to determine which groups of game elements contributed more to the overall differences. The game elements scores across games were significantly different for all groups except Artistic movement. Strategic resource management (η^2 = .075), Sports and Cards (η^2 = .080), Virtual goods (η^2 = .063), Action (η^2 = .083) and Progression (η^2 = .106) showed medium effects, whereas Puzzle (η^2 = .026), Role-playing (η^2 = .041) and Simulation (η^2 = .030) showed small effects. Figure 2 further details these effects by showing the percentiles where the participants that mentioned each game fall in relation to the whole participant sample.

	S.R.M.	Puz.	Art.	Spo.	R.P.
Median	70.83	75.00	44.44	38.89	88.89
Mean	67.69	72.71	44.45	38.14	85.14
Std. Dev.	19.95	18.46	21.49	22.57	13.38
H (KW)	87.910	53.583	37.054	91.366	63.839
p	< .001	.030	.420	< .001	.003
η^2	.075	.026	.003	.080	.041
	V.G.	**Sim.**	**Act.**	**Prog.***	
Median	72.22	80.00	70.59	75.00	
Mean	69.64	78.15	67.11	72.03	
Std. Dev.	16.71	14.92	19.73	14.02	
H (KW)	79.339	56.261	93.576	57.233	
p	< .001	.017	< .001	.008	
η^2	.063	.030	.083	.106	

Note. N = 743; df (KW) = 36.
* Due do a data collection error, data for Progression was only available in the first dataset. Thus, for this column, N = 263 and df = 34.
S.R.M. = Strategic resource management; Puz. = Puzzle;
Art. = Artistic movement; Spo. = Sports and Cards;
R.P. = Role-playing; V.G. = Virtual goods; Sim. = Simulation;
Act. = Action; Prog. = Progression.

Table 4. Kruskal-Wallis tests between Game Elements and Games.

Relationship Between Games and Game Playing Styles

The nonparametric comparison of multivariate samples showed an overall significant difference in the game playing styles scores per game: $\lambda_{(180.000,3488.281)} = 2.518; p < .001$ (for the combined dataset with $N = 743$ game mentions), which supports hypothesis **H3**.

Table 5 shows the results of the Kruskal-Wallis tests to determine which groups of game playing styles contributed more to the overall differences. The scores across games were significantly different for all playing styles. Multiplayer (η^2 = .169) and Competitive community (η^2 = .153) showed large effect sizes, whereas Abstract interaction (η^2 = .053), Solo play (η^2 = .035) and Casual play (η^2 = .036) showed small effects. Figure 3 further details these effects by showing the percentiles where the participants that mentioned each game fall in relation to the whole participant sample.

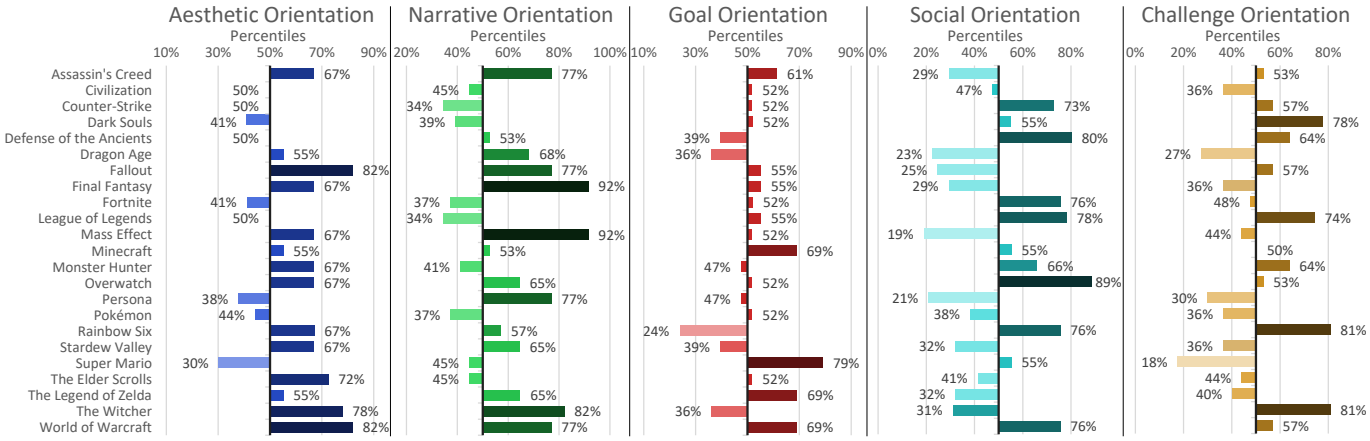
	Mul.	Abs.	Solo	Com.	Cas.
Median	58.33	62.50	83.33	52.78	66.67
Mean	55.23	62.25	83.56	52.31	60.87
Std. Dev.	25.04	18.16	13.03	21.76	27.68
H (KW)	154.184	72.586	59.663	143.248	60.675
p	< .001	< .001	.008	< .001	.006
η^2	.169	.053	.035	.153	.036

Note. N = 743; df (KW) = 36.
Mul. = Multiplayer; Abs. = Abstract interaction; Solo = Solo play;
Com. = Competitive community; Cas. = Casual play.

Table 5. Kruskal-Wallis tests between Playing styles and Games.

Relationship Between Games and Gender

The analysis of the relationship between participants' genders with their game choices also used the combined dataset with $N = 743$ game mentions, which contained 212 game mentions from women, 488 from men, and 43 from other genders. Unfortunately, we did not have enough cases from other genders



Note. The values in the charts represent the percentile rank of the scores of the players who mentioned each game. For example, a value of 80% for a combination of trait and game means that participants who mentioned said game scored higher than 80% of all participants in the sample for the same trait.

Figure 1. Percentile ranks of the Player Trait scores by Game.

to perform the chi-square test; therefore, we only included the responses from men and women in the analysis ($N = 700$). The chi-square test showed an overall significant difference in the game choices per genre: $\chi^2_{(36)} = 149.326; p < .001; V = .462$, which supports hypothesis **H4** with a large effect size.

Table 6 shows the detailed cross-tabulation between gender and games to determine which games contributed more to the overall differences between genders. The games with the strongest preference by men were *Call of Duty*, *Counter-Strike*, *Rainbow Six*, *Rocket League*, and *X-COM*, which were only mentioned by men in the sample. Thus, it is not even possible to calculate how likely they are to be mentioned by men rather than women (so, the table shows $\rightarrow \infty$). Other games with a strong significant preference by men were *Dark Souls* (12.6 times more likely to be mentioned by men than women), *Defense of the Ancients* (6.1 times more likely), and *Overwatch* (3.9 times more likely). On the other hand, games with a strong significant preference by women were *The Sims* (14 times more likely to be mentioned by women than men), *Kingdom Hearts* (9.3 times more likely), *Stardew Valley* (5.7 times more likely), *Dragon Age* (5.3 times more likely), *Persona* (3.3 times more likely), *The Legend of Zelda* (2.5 times more likely), and *Pokémon* (2.3 times more likely).

Relationship Between Games and Age

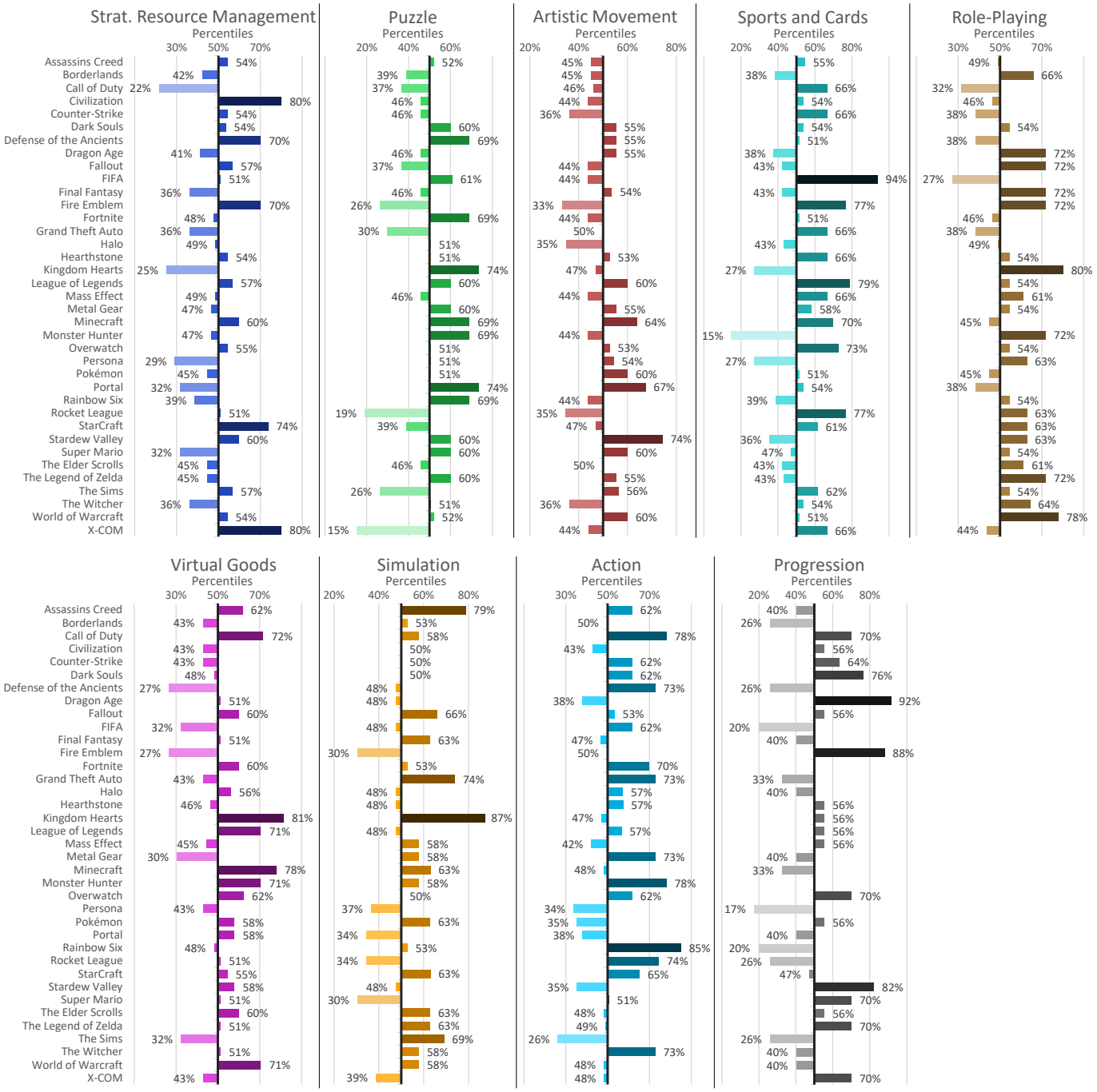
In the combined dataset ($N = 743$), the mean age was 25.27 ($SD = 7.02$), and the median was 24.0. The one-way Kruskal-Wallis test showed an overall significant difference in the participants' ages for each game name: $H_{(36)} = 109.959; p < .001; \eta^2 = .106$, which supports hypothesis **H5** with a medium-large effect size.

Table 6 shows the median ages for the participants who mentioned each game. The games mentioned more often by the oldest participants were *StarCraft* (33.0), *X-COM* (30.0), *Final Fantasy* (29.0), *Civilization* (28.5) and *Defense of the Ancients* (28.0), where the numbers in brackets are the median age for participants who mentioned each game. On the other hand, the games mentioned more often by the youngest participants were *Halo* (20.0), *Overwatch* (20.0), *Borderlands* (20.5), *Call of Duty* (21.0), *Counter-Strike* (21.0), *League of Legends* (21.0), and *Persona* (21.0).

Games	Female[a]	Male[a]	Ratio (M/F)[b]	Med. Age
Assassin's Creed	3.3%	3.1%	0.94	25.0
Borderlands	2.8%	1.2%	0.43	20.5
Call of Duty	0.0%	2.3%	$\rightarrow \infty$ *	21.0
Civilization	3.8%	3.9%	1.03	28.5
Counter-Strike	0.0%	3.9%	$\rightarrow \infty$ *	21.0
Dark Souls	0.5%	5.9%	12.60 *	23.0
DotA	0.5%	2.9%	6.08 *	28.0
Dragon Age	4.2%	0.8%	0.19 *	23.0
Fallout	3.8%	4.5%	1.19	26.0
FIFA	0.5%	2.0%	4.34	26.0
Final Fantasy	3.8%	3.5%	0.92	29.0
Fire Emblem	0.9%	1.6%	1.74	24.0
Fortnite	0.9%	1.4%	1.52	21.5
Grand Theft Auto	1.4%	2.5%	1.74	22.0
Halo	1.9%	1.2%	0.65	20.0
Hearthstone	0.9%	2.0%	2.17	23.5
Kingdom Hearts	3.8%	0.4%	0.11 *	25.0
League of Legends	2.4%	3.5%	1.48	21.0
Mass Effect	2.4%	3.7%	1.56	25.0
Metal Gear	0.5%	2.5%	5.21	26.0
Minecraft	3.3%	3.1%	0.93	25.0
Monster Hunter	0.5%	1.4%	3.04	24.0
Overwatch	1.4%	5.5%	3.91 *	20.0
Persona	3.8%	0.4%	0.11 *	21.0
Pokémon	9.0%	3.9%	0.43 *	24.0
Portal	1.9%	1.6%	0.87	22.0
Rainbow Six	0.0%	2.7%	$\rightarrow \infty$ *	23.0
Rocket League	0.0%	2.5%	$\rightarrow \infty$ *	24.0
StarCraft	0.5%	1.8%	3.91	33.0
Stardew Valley	7.1%	1.2%	0.17 *	24.0
Super Mario	3.3%	1.8%	0.56	24.0
The Sims	5.7%	0.4%	0.07 *	25.0
The Elder Scrolls	9.4%	7.0%	0.74	24.0
The Legend of Zelda	11.8%	4.7%	0.40 *	25.0
The Witcher	1.4%	3.5%	2.46	25.0
World of Warcraft	3.3%	2.9%	0.87	27.0
X-COM	0.0%	2.0%	$\rightarrow \infty$ *	30.0
N / Med. Age	**212**	**488**		**24.0**

a. Percentage of female or male participants who mentioned each game.
b. How likely it is that the game will be mentioned by a male rather than a female participant.
* Significant at the .05 level (z-test with Bonferroni correction).

Table 6. Relationships of Gender and Age with Games.



Note. The values in the charts represent the percentile rank of the scores of the players who mentioned each game. For example, a value of 80% for a combination of game element and game means that participants who mentioned said game scored higher than 80% of all participants in the sample for the same element.

Figure 2. Percentile ranks of the Game Elements scores by Game.

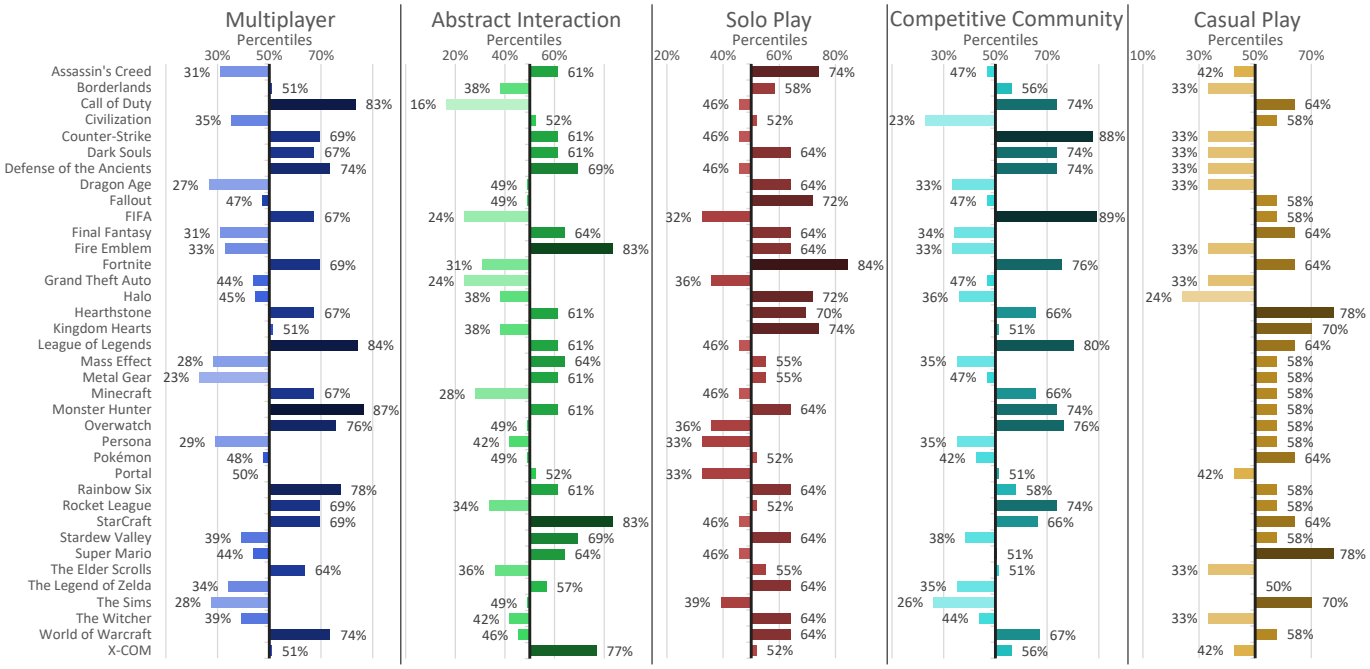
DISCUSSION

In the present work, we analyzed how the participants' player trait scores (**RQ1**), game elements and game playing style preferences (**RQ2**), and their gender and age (**RQ3**) influenced the choice of games that they like.

All our hypotheses were supported by the statistical tests, meaning that the values of these five variables are significantly different across games.

Usage of the Results

Organizing the results into a useful format, we provide a table in the supplementary material that summarizes the characteristics of players who enjoy each game. This information can be used when designing, marketing, or studying the games in the table or games similar to (or inspired by) them to better understand the characteristics of the players who are more likely to play the game.



Note. The values in the charts represent the percentile rank of the scores of the players who mentioned each game. For example, a value of 80% for a combination of playing style and game means that participants who mentioned said game scored higher than 80% of all participants in the sample for the same style.

Figure 3. Percentile ranks of the Game Playing Styles scores by Game.

For example, if a game studio decides to design a new shooter inspired by *Counter-Strike* or *Overwatch*, our results show that both games are enjoyed by younger men with high social orientation. However, *Counter-Strike* is enjoyed by players with low narrative orientation, whereas *Overwatch* is enjoyed by players with high narrative and aesthetic orientations. Therefore, the studio can decide if they want players to focus on a narrative or not. This decision will affect game design and marketing segmentation.

Similarly, if a game studio decides to create a new role-playing game inspired by *Final Fantasy* or *The Witcher*, our results show their players have high aesthetic and narrative orientation. However, *Final Fantasy* players usually have lower challenge orientation, whereas *The Witcher* players enjoy challenges. Thus, the decision to create a more or less challenging game would help the studio decide if they should be more inspired by *Final Fantasy* or *The Witcher*. Furthermore, knowing that *Final Fantasy* players are older and with a balanced gender distribution, whereas *The Witcher* is more enjoyed by men, can help direct marketing efforts for games inspired by them.

Relationship Between Games and Player Traits

Undoubtedly, the social aspects contributed the most to different game choices by participants. Social orientation was the most relevant player trait, with a large overall difference between games. Similarly, Multiplayer and Competitive Community were the most relevant playing styles. Tondello et al. [72] have previously shown that there are significant correlations between social orientation and preferences for multiplayer gaming and competitive gaming communities. Therefore, it is not surprising that the scores for these variables are similar for players who enjoy the same games.

The preferred games for participants of high social orientation and preference for multiplayer gaming and competitive communities were *Call of Duty*, *Counter-Strike*, *Defense of the Ancients*, *FIFA*, *Fortnite*, *League of Legends*, *Overwatch*, *Rainbow Six*, and *World of Warcraft*. All of these games are intended to be played in multiplayer mode, or at least support it, and there are active competitive gaming communities for most of them. On the other hand, participants with low social orientation and low preference for multiplayer gaming and competitive communities prefer games such as *Civilization*, *Dragon Age*, *Fallout*, *Final Fantasy*, *Mass Effect*, *Persona*, and *The Sims*. Interestingly, most games on this list feature aspects of role-playing or simulation with strong narratives, and are enjoyed by players with higher narrative orientation scores. It seems that the immersive characteristic of these games makes them enjoyable without needing the presence of other players.

The outlook of the scores for aesthetic and narrative orientations are similar between games, which is to be expected because there is a medium correlation between these player traits (see [72]). The games preferred by participants with high aesthetic and narrative orientations were *Assassin's Creed*, *Fallout*, *Final Fantasy*, *Mass Effect*, *The Witcher*, and *World of Warcraft*. This makes sense because all these games feature large worlds and intricate narratives that the player can explore and immerse into. Interestingly, there were not many games with low scores for these traits, but these include *Dark Souls*, *Fortnite*, *Pokémon*, and *Super Mario*. There are also some games for which the median scores differ considerably for these traits, such as *Counter-Strike*, *League of Legends*, *Persona*, and *The Elder Scrolls*. This reinforces Tondello et al.'s [72] argument that these traits should be kept separated despite the partial correlation between them.

For challenge orientation, the games preferred for players with high scores were *Dark Souls*, *League of Legends*, *Rainbow Six*, and *The Witcher*, which are all recognized by their difficulty. Contrarily, games preferred by players with low challenge orientation include *Dragon Age*, *Persona*, and *Super Mario*.

Regarding goal orientation, the differences in scores between games were not significant in overall. However, the scores deviated considerably for a few games: *Minecraft*, *Super Mario*, *The Legend of Zelda*, and *World of Warcraft* showed the highest goal orientation scores, whereas *Rainbow Six* showed the lowest scores. This trait may be less important for game selection because all games offer some sort of goals, thus appealing for players with a broad range of goal orientation. Therefore, scores in this trait may influence more the way that the player interacts with a game (trying to complete all optional goals or ignoring them, for example) instead of what games they play. The exception seems to be for games that explicitly focus on the achievement of goals, such as *Super Mario* or *World of Warcraft*. The fact that *Minecraft* was mentioned by players with high goal orientation is interesting, considering that the game does not offer pre-defined goals, but lets players define their own goals. The reason may be that precisely because all goals are optional, only players who are highly driven by their self-defined goals enjoy the game.

Relationship Between Games, Gender and Age

Together with the social preferences, gender was the other variable that accounted for the different game choices with a large effect size. The games that were mentioned more often by men were *Call of Duty*, *Counter-Strike*, *Dark Souls*, *Defense of the Ancients*, *Overwatch*, *Rainbow Six*, *Rocket League*, and *X-COM*. On the other hand, the games that were mentioned more often by women were *Dragon Age*, *Kingdom Hearts*, *Persona*, *Pokémon*, *Stardew Valley*, *The Sims*, and *The Legend of Zelda*. Looking at these lists, it seems that men are more attracted to intense, challenging, or competitive games, whereas women are more attracted to immersive and relaxed games. This is inline with previous findings (see [73]).

Finally, age was also significantly different across games with a medium effect size. However, participants in our sample were rather young in average, with the median age between games varying only between 20 and 33. While it is difficult to derive a clear pattern from the data, it seems that strategy games such as *StarCraft*, *Civilization*, and *X-COM* generally appeal to an older audience. On the other hand, first-person shooters such as *Overwatch*, *Call of Duty*, and *Counter-Strike* seem to appeal more to younger audiences.

Comparison with Previous Work

In comparison with Tondello et al.'s [73] previous study, we now reinforce the evidence that the studied player characteristics significantly influence their game choices, while also observing stronger effects. One reason for larger differences in player trait scores by games in our study may be that we used a new and more reliable version of the player traits scale. Therefore, our results further support the validity of the player traits and its new measurement scale [72] as an indicator of player preferences. We also reinforce their other two conclusions: (1) that multiple factors need to be considered when predicting player preferences for different games; and (2) game genre alone is not enough to determine player preferences because games of similar genres might have distinct player profiles.

Vahlo et al. [79] also showed that player types are related to game choices. However, it is difficult to directly compare their results with our work because they used a different player types model and only asked about game genres, not individual games. Our results are more specific because we related several player characteristics with individual games.

Quantic Foundry [87] also has a rich dataset on game choices and player characteristics, but their data and results are proprietary. Even so, we compared our results with the data that is publicly available from them [89, 91]. The detailed comparison is in the supplementary material.

Limitations

Like any survey that relies on participants' self-reported answers, the accuracy of our analyses depends on the accuracy of the responses. However, the fact that meaningful relationships have been observed between related constructs, such as player traits, preferred game elements, and preferred games, provides good evidence in favour of the acceptance of these models and the collected participant data. Another characteristic of our study is that we were limited to analyzing the games that were mentioned more often by participants, which may have left many popular games out of the study. Future studies with larger samples will allow us to verify how well these findings can generalize to different people and further use our method to study a larger variety of games.

CONCLUSION AND FUTURE WORK

Our work provides evidence that player trait scores, preferred game elements and playing styles, gender, and age can significantly explain players' preferences for different games.

In future work, we will continue collecting more data about more games and players. This will allow us to better predict what games a player is likely to enjoy given their traits and preferences, or to generally describe the profiles of the players who enjoy each game. Additionally, we will investigate the relationship between players' traits and preferences with their behaviour within games, so we can also understand how the characteristics of the player influence how they play games.

A relevant finding from this study is that goal orientation scores did not affect game choices as much as other traits. We believe that this may be because most games still allow players to pursue goals, even if they are self-defined. Future studies could refine the goal orientation trait to differentiate players who prefer game-defined or self-defined goals.

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