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CHAPTER 2

Two Overwatch Player Profiles

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Introduction

What are Overwatch players like? The goal of this chapter is to map out surface characteristics of those who play Overwatch in order to better understand the game and its players' roles in the larger context of esports play and players. To do this, we employ relatively large-scale esports survey data and carry out game-specific cluster analysis: the surveyed players are divided into groups, which are identified based on the players' gaming habits. Ultimately, our study will identify six esports player clusters, two of which include distinct Overwatch players. By comparing these two Overwatch player clusters with each other as well as with other esports player clusters, this chapter sets hypotheses that help interpreting the rest of this book's chapters and, we hope, also the accumulating and diversifying literature on esports players more widely.

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Esport Players and Overwatch

Although the focus of this chapter is not so much on Overwatch as it is on its players, a few words about the game's identity are in order. First, it is important to acknowledge that Overwatch was released in 2016—a year before Fortnite but several years after now-canonical Counter-Strike, Dota 2, and League of Legends—which is important to keep in mind when assessing its players who have moved to play Overwatch from other similar titles, and *vice versa*. Second, we highlight the hybrid design of Overwatch as a game—with a clear competitive esports scene and at the same time also an evolving transmedia universe with a rich character pool and lore (Koskimaa et al. 2021)—which suggests that the profiles of Overwatch players might be more diverse than those of many other similar competitive games. In particular, the premise that the game's audience is strongly polarized between "casual" and "core" players (see Blamey in this volume) makes it an interesting case study.

Perhaps the most problematic convention in contemporary esports research is the equation of the phenomenon with "professional gaming" (instead of the more descriptive "competitive gaming"). As in any other game or sport, players can become professionals by various standards; however, most participating individuals typically engage with an amateur, casual, fan, or semi-serious attitude without ever even dreaming of professional careers. Accordingly, when we speak of esports and Overwatch players, we are not exclusively interested in professionals (see, e.g., Chung et al. 2019; Zhou and Zhou 2020; Rudolf et al. 2020).

Previous research on esports has identified several participatory tendencies. Whereas some players enjoy these games primarily as a social activity or media that allows them to see others play (e.g., Seo and Jung 2016; Siutila 2018; Taylor 2018), a significant number of people play with clear competitive goals (e.g., Martončik 2015; Nagorsky and Wiemeyer 2020; Karhulahti 2020). Games like Overwatch also support player experiences that involve narrative or worldbuilding elements, which complicates the potential modes of engagement still (e.g., Blom 2018; Välisalo and Ruotsalainen 2019; Gandolfi and Antonacci 2020).

The idea that players play multiple games with multiple styles—sometimes at the same time—has been a premise in games research for a long time. Over the past decades, researchers have developed various player typologies and behavior models that aim at understanding the increasing diversity of players and play styles (e.g., Kallio et al. 2011; Park et al.

2011). Along with the ever-growing number of new videogames and players, such genre- or videogame-specific models often struggle to remain relevant, however (Cowley and Charles 2016). Accordingly, in this study we do not rely on any specific hypotheses or stereotypes regarding Overwatch players but rather start with a simple premise: many contemporary players of videogames play Overwatch, and it is possible that such Overwatch players differ from the rest in respect to their gaming habits, motivations, or other variables.

Data and Method

A survey was organized in 2019 to investigate videogame player preferences. The survey data (N = 1506, ages 18–75) was collected via a UK-based crowdsourcing platform Prolific that holds an online panel of approximately 70,000 users in multiple countries. Two samples from the UK (n = 1089) and the USA (n = 417) were collected simultaneously by using identical questionnaires. The surveys included questions about played videogames, genre preferences, gaming motivations, experiences, and gameplay, as well as challenge preferences. In addition to this, the surveys included background questions about the respondents' age, gender, weekly play time, and money spent in gaming during a typical month.

Because we did not receive financial support for the data collection of this study, the assistance provided by Prolific was compensated by a collaborating data analytics company which now owns the data; thus, we cannot share the data publicly. The study did not require a local ethics committee statement.

The surveys in both countries were targeted only to those participants who had previously specified to be at least a bit interested in playing videogames (1 = Not at all interested, 2 = Only a little interested, 3 = Moderately interested, 4 = Interested, 5 = Very interested). Prolific cleaned the data from those respondents who had answered the survey too quickly. Those participants who had submitted incomplete responses were also excluded, and therefore the final sample did not contain any missing values.

We were interested in player preferences and profiles of five videogames in particular: Overwatch, Fortnite, League of Legends, Dota 2, and Counter-Strike. We address these titles as "esport games" with "esport players" to highlight their specific competitive features, but acknowledging that the label "esport" also simplifies what the games and players are (see later). Survey participants were then asked to report how much they

had played each title (0 = Not at all, 1 = Only a little, 2 = Moderately, 3 = Quite much, 4 = Very much). A total of 731 survey participants reported to have played one or more of the five esports games at least a little (1–4). We used this information to generate subsamples of esports players (n = 731, 48.5%) and non-esports players (n = 775, 51.5%). Descriptive statistics of the overall sample and the esports subsample are reported in Table 2.1.

Since the focus of this chapter is on Overwatch players, we do not analyze the overall sample or the esports subsample in detail. However, it is worth noting that esports players spend significantly more money and time on gaming than non-esports players. Also, as a general remark, our sample is clearly biased on players who identify as females, which we consider a significant benefit for the study. With reference to previous large-scale studies that have found women representing as low as 4.1% of certain active esports populations (e.g., Ratan et al. 2015), our subsample is uniquely balanced with a somewhat equal gender representation among

Table 2.1 Descriptive statistics of the sample of this study (N = 1506) and the subsample of esports players (n = 731)

	UK	*USA*	*Total*
All respondents	1089	417	1506
Male	374	169	543
Female	705	243	948
Other	8	5	13
Not disclosed	2	0	2
Mean age	38.1	34.3	37
Weekly play (hours), Computer	2.4	3.7	2.7
Weekly play (hours), Console	2.1	2.3	2.1
Weekly play (hours), Mobile	2.3	2.1	2.3
Money spent each month	19.8	27.1	21.7
Esports players	484	247	731
Male	239	138	377
Female	241	104	345
Other	3	5	8
Not disclosed	1	0	1
Mean age	34	31	33
Weekly playtime/Computer	3.8	4.9	4.2
Weekly playtime/Console	3.2	2.9	3.1
Weekly playtime/Mobile	1.8	1.7	1.7
Money spent each month	33.3	39.1	35.1

those who play esports games. Due to the major differences between esport titles and the rapid evolution of esports cultures, we cannot know to what degree our gender balance represents the reality of esports or Overwatch players.

Lastly, we must also make a note about our respondents' age: although the average age of our esports players (33 years) is well in line with the steadily increasing average age of videogame players, it is clearly higher than those of other recent studies. For instance, in a large German convenience sample of esports players collected in popular online sites (Rudolf et al. 2020) the average age was 23 years (92% male), and in a similar English sample (Nagorsky and Wiemeyer 2020) the average age was 21 years (95% male). Elite or high-level players have been reported to be even younger, below 21 years (97% male) (Kari et al. 2019). Because our sample was collected via Prolific and the adult population only, it is likely that the collection method explains a large part of this difference; however, in the same way as with gender, we have no way of knowing what the true average age of esports players is in general or in Overwatch. Whereas the above gender aspect likely explains some of this variation, we cannot know if the popular online esports sites, which produce young, nearly all-male samples, represent the reality of all players or if such online sites are more used by this demographic in particular.

Measures

The survey included three psychometrically validated measures. We report Cronbach's alphas for each scale and factor in parentheses. Intrinsic Motivations to Gameplay (15-IMG) inventory measures how important a set of motives are for one's videogame play (1 = Not important at all, 5 = Very important). The inventory consists of five factors. *Relatedness* (α = 0.89) measures social motives such as playing because friends play. *Competence* (α = 0.72) consists of motives such as playing because of challenge. *Immersion* (α = 0.82) measures motives such as playing to identify with in-game characters. *Fun* (α = 0.78) measures to what extent one plays because gaming is entertaining. *Autonomy* (α = 0.84) measures motives to play because one can experience, for example, freedom (Vahlo and Hamari, 2019).

Challenge Types in Gaming (12-CHA) is a 5-point scale for measuring sustaining player preferences in four types of challenges (1 = very unpleasant, 5 = very pleasant). *Physical challenges* (α = 0.77) assess preferences in

kinesthetic challenges such as fast reaction. *Analytical challenges* ($\alpha = 0.78$) consist of problem-solving. *Socio-emotional challenges* ($\alpha = 0.82$) cover moral and ethical challenges. *Insight challenges* ($\alpha = 0.72$) measure preferences in stable tasks such as puzzles (Vahlo and Karhulahti 2020).

Gameplay Activity Inventory (15-GAIN) is a 5-point measure (1 = very unpleasant, 5 = very pleasant) for assessing preferences in activity types that contemporary videogames present. *Aggression* ($\alpha = 0.94$) measures preference in, for example, killing, sniping, and shooting. *Caretaking* ($\alpha = 0.83$) includes activities such as dressing up and hanging out with friends. *Coordinate* ($\alpha = 0.85$) consists of activities such as performing in athletics, racing, and running. *Exploration* ($\alpha = 0.88$) covers activities such as developing characters and collecting rare items. *Management* ($\alpha = 0.88$) assesses preference in activities such as construction and crafting (Vahlo et al. 2018).

Due to Overwatch's reputation as a game with a diverse audience, we also included six questions about the players' preferred game experience types. Survey participants were asked to state how pleasant the following game experiences were for them (1 = very unpleasant, 5 = very pleasant): "Experiences of hardcore gaming which really tests your skills and wits", "Experiences of laid-back relaxing casual gaming", "Experiences of competitive gaming in which you want to win", "Experiences of story-driven gaming in which you focus especially on the fiction of the game", "Experiences of short-term gaming which offers a little break to your everyday routines", and "Experiences of intensive and long-term gaming without any interruptions". In what follows, we will call these items with shorter names: "hardcore", "casual", "competitive", "story-driven", "short-term", and "long-term" game experiences.

Finally, in addition to the above validated measures, the surveys also included a set of questions about what the participants have played and how much. We asked the participants to report how much they had played the genres of action games, action-adventure games, adventure games, racing, role-playing, platformers, puzzles, sports, simulation, and strategy (1 = Not at all, 5 = Very much). Specific videogame titles had to be named, including the mentioned esports games.

Esports and Correlations

We start by reporting the distribution of the esports games within the subsample (Table 2.2). First, a total of 47.2 % ($n = 345$) of our esports players reported that they play Overwatch. Of these Overwatch players,

Table 2.2 Esports players of the sample (n = 731) and their esports-related play behavior

N = 731	*n*	*Only a little*	*Moderately*	*Quite much*	*Very much*	*Mean*
Counter-Strike	354	133	84	64	73	2.1
Dota 2	175	72	43	24	36	1.5
Fortnite	524	207	142	82	93	2.5
League of Legends	297	113	70	45	69	1.9
Overwatch	345	92	97	59	97	2.2

Those who responded "Not at all" are not included in this table

32 played *only* Overwatch whereas the remaining 313 also played some of the other esports games. Similarly, only five players reported that they played *only* Dota 2 and 27 players reported to play *only* League of Legends. Finally, 51 told that they play only Counter-Strike. Fortnite was an exception, as no less than 187 survey respondents reported this to be their only esports game.

Based on the above initial results, our first finding is that, more likely than not, the most common type of Overwatch player is not *only* an Overwatch player, but rather a player who plays Overwatch as one of their esports games. Again, we highlight that (due to our limited sample) there can be a large number of players who play Overwatch as their sole esports game, however, compared to this unknown number, the number of those who play Overwatch *as one of their two or more esports games* is larger—probably multiple times larger. The same seems to concern other esports titles too, with the possible exception of Fortnite.

Because reliable statistical analysis of our 32 Overwatch-only players would not be possible with the present methods, we pursued the analysis based on (Pearson's) correlations between the five esports games (Table 2.3). As for these correlations, Overwatch play was moderately or strongly correlated with every other esports game play, and the same was true for Counter-Strike, League of Legends, and Dota 2. Also, Fortnite play was correlated with a habit to play other games, but these correlations were not as strong as those between other esports games.

To better identify those players who play Overwatch as one of their esports games, we continued to explore their profiles with an explorative approach, enabled by a cluster-analysis procedure.

Table 2.3 Esports game players of the sample (n = 731) and their esports game play behavior

	Overwatch	*Fortnite*	*League of Legends*	*Dota 2*
Overwatch				
Fortnite	0.466			
League of Legends	0.530	0.426		
Dota 2	0.491	0.362	0.491	
Counter-Strike	0.507	0.400	0.502	0.519

All of the reported correlations are statistically significant on the level of $p < 0.001$

Table 2.4 Esports player clusters, constructed based on questions about survey respondents' habits to play the five esports games

	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*	*Cluster 6*	*NA**
N	93	112	53	242	131	81	19
Play freq. standardized							
Overwatch	1.05	-0.16	-0.24	-0.52	0.87	-0.20	
Fortnite	1.03	-0.63	-0.44	1.89	-0.60	0.84	
League of Legends	-0.37	-0.24	-0.71	-0.35	0.74	-0.63	
Dota 2	-0.90	-0.64	1.11	-0.52	-0.57	-1.12	
Counter-Strike	-0.81	1.67	0.28	-0.50	-0.45	1.10	
Esports play mean	2.40	1.86	2.75	1.58	1.97	2.45	
Play freq. mean value							
Overwatch	3.56	1.76	2.51	1.17	2.92	2.28	
Fortnite	3.54	1.26	2.26	3.05	1.33	3.30	
League of Legends	2.01	1.68	2.17	1.34	2.76	1.83	
Dota 2	1.40	1.24	3.87	1.16	1.34	1.28	
Counter-Strike	1.49	3.37	2.96	1.18	1.5	3.57	

Cluster Analysis

An exploratory cluster analysis with Stata 14.2 software was carried out to investigate how players differ in their habits to play esports games. Those readers who are not interested in the actual analysis procedure may skip the below paragraphs and jump directly to the point after Table 2.4 where we describe each cluster that the analysis produced.

We began the clustering process by computing z-standardized response scores for each of the five esports per survey participants. Standardizing is considered an important step in analyses in which a specific variable in the analysis may dominate the results (Everitt et al. 2011). In the case of our

study, we wanted to make a cluster analysis which would not be affected by how much a respondent reported playing any of the five esports games *in total*. Instead, we were more interested in identifying esports player profiles based on the respondents' relative esports gaming profiles, that is, if they would play a specific game more than other four games, or, for instance, two games clearly more than the rest of them. If we would have made a cluster analysis with non-standardized data, the analysis would very probably have resulted in heavy esports players, moderate esports players, and light esports players, which would have not been the most informative solution for our study.

By standardizing esports game play responses for each survey participant, we generated a 0-value for each participant and then investigated how a participants' own esports game responses compared to this relative 0-value. As an analysis procedure, standardization excludes data from cluster analysis; in our case, the amount of playing esports games in total. However, this information was included in the following steps of analysis when we interpreted the results of the cluster analysis.

Next, we examined the data to get the optimal cluster solution. This is usually done by using a scree plot and searching for anomalies (a kink) in the curve that is generated from the within sum of squared (WSS) or its logarithm [log(WSS)] for all examined possible cluster solutions (Makles 2012). We examined both of these methods and decided to construct six player clusters as both WSS and log (WSS) suggested a six-cluster solution.

We then conducted a k-means clustering for a six-cluster solution. K-means is a partition cluster-analysis method by which observations are grouped into a distinct number of groups that do not overlap. In the grouping procedure, observations are grouped together with those observations which share the closest means. In our case, these closest means were the standardized profiles of esports play. Since we decided to construct six clusters, the k-means procedure utilized this criterion and grouped each observation into one of these groups. We used k-means instead of hierarchical clustering models because we did not have expectations of a latent hierarchical structure. Indeed, clustering methods are tools for generating hypotheses rather than for testing them (Everitt et al. 2011). Descriptive statistics of the background variables for each player type are presented in Table 2.4.

In **Cluster 1** (n = 93, 12.7%) participants reported to play Overwatch more than participants of the other five clusters. However, they reported playing Fortnite equally much. These players had the third-highest esports

play mean value. Participants of **Cluster 2** (n = 112, 15.3%) can be labeled Counter-Strike players, as these players showed low values for all the other four games. **Cluster 3** (n = 53, 7.2%) was the smallest identified player cluster. These players had the highest esports play mean value and they reported playing Dota 2 in particular. **Cluster 4** (n = 242, 33.1%) was the largest cluster. The players in this cluster reported to play only Fortnite, and they also had the lowest esportsS mean of the six groups. **Cluster 5** (n = 131, 17.9%) reported to play League of Legends more than the other player clusters, but also Overwatch. They did not play Overwatch as much as players in the first cluster, however. In **Cluster 6** (n = 81, 11.0%), people played Counter-Strike and Fortnite, and they had the second-highest esports mean value. Based on the above, this chapter's focus will be on how the first cluster (**OW1** = people who play Overwatch and Fortnite) and the fifth cluster (**OW2** = people who play Overwatch and League of Legends) differ from each other as well as from the rest of the clusters (Table 2.5).

We should also note that a total of 19 survey respondents reported to play all five esports games equally much (marked with * in Table 2.4). While this is an interesting result in itself, their gaming behavior also means that they do not have an esports gaming profile similar to the

Table 2.5 Esports player clusters, constructed based on questions about survey respondents' habits to play the five esports games

	OW1	*C2*	*C3*	*C4*	*OW2*	*C6*	*Non*
n	93	112	53	242	131	81	794
UK (n = 1089)	5.4%	6.8%	2.9%	17.5%	6.2%	4.8%	56.4%
USA (n = 417)	8.2%	9.1%	5.0%	12.2%	15.4%	7.0%	43.2%
Male %	50.5%	69.6%	62.3%	36.4%	43.5%	74.1%	22.7%
Female %	48.4%	28.6%	37.7%	63.6%	51.9%	25.9%	76.6%
Other %	1.1%	0.9%	0.0%	0.0%	4.6%	0.0%	0.6%
Not disclosed %	0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	0.1%
Age	32.97	32.63	28.57	35.51	30.86	32.74	40.6
Money spent/month ($)	47.4	29	35.3	26.2	37.6	48.3	10.5
Weekly play hours							
With computers	5.3	5.1	5.9	1.6	5.6	6	1.4
With consoles	4.8	2.0	2.4	2.8	2.5	4.5	1.3
With mobile phones	2.3	1.4	0.9	2.1	1.6	1.6	2.7

remaining 719 survey respondents. We decide therefore to exclude these respondents from the remaining analyses.

Data Analysis

Before moving to analyze the two Overwatch clusters in more detail, it is worth highlighting that some players of the four other clusters had played Overwatch too. In other words, our results yield evidence for a hypothesis that people who play esports games, like Overwatch, do at least experiment with multiple titles. That said, the six-cluster product also indicates that, when it comes to people's esports habits, they do clearly prefer some titles over others and usually commit to one or two. As for Overwatch, the most common profiles surface as players whose playtime is primarily shared between Fortnite (**OW1**) and League of Legends (**OW2**).

As we now move to look at these two clusters more closely, let us start with demographics and other more general variables. First, we observe that both Overwatch clusters are well balanced in terms of gender, which is not the case with the Counter-Strike (C2), Dota 2 (C3), and mixed (C6) clusters that all have a strong male bias. The Fortnite cluster (C4), however, had even more of its players identify as female. It is possible that Overwatch and Fortnite appeal to women players more than many other esports games do.

The average age of an Overwatch player in **OW1** is 32.3 years and in **OW2** 30.9 years. We ran paired t-tests to determine if there were statistically significant differences in the mean ages between these two clusters and between them and the other four clusters. There was a statistically significant difference in both cases, between **OW1** and **OW2**, $t(222) = 1.65$, $p < 0.05$, Cohen's $d = 0.22$ (CI 95%) as well as, for instance, between **OW1** and C3, $t(144) = 2.84$, $p < 0.005$, Cohen's $d = 0.489$ (CI 95%).

Furthermore, we observe a key difference between the two Overwatch clusters: in the first one (**OW1**), players play more on their console than any other esports cluster (4.8 hours per week), whereas in the second one (**OW2**) console gaming is somewhat average (2.5 hours per week). This is important to keep in mind, as we move to examine the Overwatch players' motives, spending, and preferences.

As for the money that Overwatch players spend on gaming, their average monthly expenditures of US $47.4 (**OW1**) and US $37.6 (**OW2**) were outnumbered only by the mixed cluster (C6). Considering that the

players in the mixed cluster also play Overwatch significantly (with other esports), it seems that Overwatch players are at the top of the esports hierarchy in terms of spending. The fact that Overwatch—unlike the other listed esports—is not a free-to-play game might contribute to this, but our data and analysis cannot produce answers to that hypothesis directly. We thus investigated the titles further with a linear regression between the habit of playing the five esports games and money spent on playing videogames. We also included gender, age, and squared age to the model as confounding variables to better understand the specific effect of esports game playing habits on spending money on gaming.

We included in the model reported in Table 2.6 the full sample of 1506 survey respondents to be able to analyze the effect of esports game play on spending money on games. The model explained approximately 10% of the variance in the variable reporting money spent per month. Three of the independent variables included in the model had a statistically significant and very similar effect on spending: Counter-Strike, Fortnite, and Overwatch play. Playing Dota 2 or League of Legends did not have a significant effect on spending, and the same was true for age, squared age, and gender.

Table 2.6 A linear regression on the impact of playing esports games, age, squared age, and gender on spending money on games ($N = 1506$)

Spending on games	*Coef.*	*Std. err.*	*t*	*p*	*β*
Counter-Strike	4.21	1.06	3.98	0.000	0.13
Dota 2	-1.05	1.38	-0.76	0.449	-0.02
Fortnite	3.28	0.85	3.84	0.000	0.11
League of Legends	1.31	1.09	1.21	0.227	0.04
Overwatch	3.59	0.98	3.67	0.000	0.12
Age	0.19	0.41	0.47	0.641	0.07
Age, squared	0.00	0.00	-0.69	0.489	-0.10
Female	-2.70	23.80	-0.11	0.910	-0.04
Male	-1.48	23.82	-0.06	0.950	-0.02
Non-binary	-7.99	25.50	-0.31	0.754	-0.02

Beyond Esports Genres

To better understand Overwatch players' gaming habits in general, we asked them to rate their videogame genre preferences. We employed a conventional 10-genre model, as noted earlier. A one-way analysis of variance (ANOVA) and Bonferroni multiple comparisons were run to examine if the mean genre play values between the six clusters varied in a statistically significant way (Table 2.7). The ANOVA test confirmed statistically significant differences between groups on their genre play average $F(5, 599) = 5.00$, $p < 0.0001$, and we continued to explore differences in the level of specific genre play between groups. In addition to showing statistically significant differences compared to each other, all clusters had significantly higher mean values for action, action-adventure, adventure, and role-playing genres than those players ($n = 794$) who did not play esports games at all. For instance, a pairwise t-test between esports players and non-esports players was $t(1258) = 18.04$, $p < 0.001$, Cohen's $d = 1.02$ (CI 95%). In contrast to this, the non-esports player group had a statistically significantly higher mean value for the puzzle genre than any of our esports clusters $t(1258) = 10.03$, $p < 0.001$, Cohen's $d = 0.57$ (CI 95%).

As for the identity of the two Overwatch clusters, our genre analysis yields one central finding. As a general tendency in the first cluster (**OW1**), players in this group have a relatively high liking for all ten genres,

Table 2.7 Clusters constructed based on the questions about the respondents' habits to play the five esports games

	OW1	*C2*	*C3*	*C4*	***OW2***	*C6*	*Non*
n	93	112	53	242	131	81	794
Action	3.7	3.5	3.3	3.0	3.4	3.8	2.2
Action-adventure	3.8	3.5	3.6	3.0	3.6	3.7	2.3
Adventure	3.7	3.5	3.7	3.3	3.7	3.7	2.6
Racing	**2.8****	2.2	2.3	2.4	**2.2****	2.5	1.8
Puzzle	3.3	3.0	2.8	3.5	3.2	3.0	3.9
Role-playing	3.6	3.3	3.7	2.8	3.8	3.5	2.4
Simulation	3.3	2.9	2.8	3.0	3.1	3.3	2.5
Sports	**2.5****	2.0	1.8	2.3	**2.0****	2.7	1.6
Strategy	**3.0****	3.5	3.5	3.3	**3.5****	3.4	3.1
Platformer	2.8	2.6	2.8	2.5	2.6	3.0	2.2

"Non" refers to those players ($n = 794$) who did not report to play any of the esports games. Bolding refers to significant differences between OW clusters (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$)

especially in comparison to the second Overwatch cluster (**OW2**). Although the genre play average of **OW1** (3.23, SD 0.58) was not higher than the genre average for **OW2** (3.13, SD 0.59) in a significant way, there were three genres that had statistically significantly different means between these OW clusters, namely racing [$t(184) = 2.72$, $p < 0.01$, Cohen's $d = (0.40)$], sports [$t(184) = 2.43$, $p < 0.01$, Cohen's $d = (0.36)$], and strategy [$t(184) = -2.70$, $p < 0.01$, Cohen's $d = (-0.40)$] with 95% confidence interval.

Here we also recall that the first cluster had the highest console usage amounts of the entire esports subsample. These observations imply that **OW1** represents a more omnivorous Overwatch player type, that is, these players seem to have a more diverse liking to different types of gaming—including a significantly higher preference for racing and sports games—with the exception of strategy videogames (this can be explained by the fact that **OW2** players were also heavy League of Legends players, which is sometimes classified as strategy). Whereas **OW1** players clearly play Overwatch and Fortnite more than other esports games, their general gaming preferences have a wide range. Since we did not explicitly ask about the players' time spent on Overwatch, we cannot know if, for instance, **OW1** are less committed to Overwatch *per se* than the players of **OW2**. We move on with this hypothesis, as we next look at the players' other preferences and motives (Table 2.8).

Preferences and Motives

For preferences and motives, too, one-way analysis of variance (ANOVA) and Bonferroni multiple comparisons showed significant differences between the esports clusters. These differences were the most significant in the case of the preferences in aggressive gaming activities ($F(5, 592) = 13.00$, $p < 0.001$, CI 95%), followed by the preferences for caretaking ($F(5, 592) = 2.7$, $p < 0.05$, CI 95%), exploration ($F(5, 592) = 4.58$, $p < 0.001$, CI 95%), and coordination ($F(5, 592) = 5.89$, $p < 0.001$, CI 95%) as part of gaming experiences. The clusters also showed differences in terms of insight challenges, and whether the players considered immersion to be important for them. Once more, the differences were more remarkable between esports players and non-esports players than among the esports player clusters.

Here, the first cluster was, again, significantly more diverse with caretaking and coordination having the highest values among all esports

Table 2.8 Player clusters, their motives to play digital games, and their preferences in challenge types, in-game activity types, and game experience types

	OW1	*C2*	*C3*	*C4*	*OW2*	*C6*	*Non*
n	93	112	53	242	131	81	794
Motives to play							
Relatedness	3.23	3.00	3.40	2.84	3.15	3.14	2.11
Competence	3.72	3.77	3.73	3.72	3.83	3.96	3.42
Immersion	2.91	2.79	3.13	2.42	3.00	2.94	1.98
Fun	4.48	4.46	4.30	4.23	4.45	4.47	4.18
Autonomy	3.16	3.09	3.36	2.78	3.18	3.14	2.44
Challenge pref.							
Analytical	3.98	3.96	3.80	3.91	3.92	4.01	3.76
Socio-emotional	**3.48***	3.24	3.36	3.18	**3.24***	3.29	2.77
Insight	3.62	3.36	3.30	3.79	3.44	3.61	3.75
Physical	**3.19****	3.14	3.15	3.14	**2.85****	3.28	2.59
Activity pref.							
Aggression	3.19	3.36	3.33	2.86	3.17	3.65	2.17
Caretaking	**2.78***	2.28	2.49	2.59	**2.53***	2.45	2.32
Coordinate	**3.08*****	2.74	2.83	3.01	**2.66*****	3.04	2.43
Exploration	3.81	3.60	3.67	3.53	3.89	3.77	3.13
Management	3.22	3.45	3.39	3.14	3.35	3.45	2.64
Experience pref.							
Hardcore	3.39	3.37	3.35	3.27	3.43	3.62	2.60
Casual	4.09	3.97	3.72	3.89	3.94	4.07	3.89
Competitive	3.48	3.41	3.52	3.52	3.39	3.58	2.88
Story-driven	4.01	3.86	3.65	3.60	4.04	4.01	3.16
Short-term	3.85	3.84	3.70	3.88	3.79	3.95	3.94
Long-term	**3.36***	3.65	3.59	3.28	**3.64***	3.68	2.74

"Non" refers to those players (n = 794) who did not report to play any of the esports games. **Bolding** refers to significant differences between OW clusters (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$)

players. Furthermore, with a 95% confidence interval, **OW1**'s mean value for both caretaking [$t(184) = 1.86$, $p < 0.05$, Cohen's $d = 0.28$] and coordinate [$t(184) = 3.54$, $p < 0.001$, Cohen's $d = 0.52$] was significantly higher than that of **OW2**. Regarding challenge type preferences, **OW1** had significantly higher preference for socio-emotional challenges [$t(184) = 1.71$, $p < 0.05$, Cohen's $d = 0.25$] and physical challenges [$t(184) = 2.39$, $p < 0.01$, Cohen's $d = 0.35$] than **OW2**. There was a significant difference in Overwatch players' preferences in long-term intensive game experiences [$t(184) = -1.66$, $p < 0.05$, Cohen's $d = -0.24$]. But general motives to play videogames for **OW1** and **OW2** were essentially

the same and did not show statistically significant differences between the clusters. Of note, there were no significant differences between the esports clusters in terms of self-reported casual and hardcore preferences.

Finally, we made multiple regression analyses on the effect of the OW clusters, age, squared age, and gender on the variables that had significantly different means between the OW clusters. Due to spatial limits, the details of these analyses are provided elsewhere (https://osf.io/f9jg2/); however, the results largely supported what we reported in Tables 2.7 and 2.8. Accordingly, our analysis points to two popular Overwatch player types: those who play Overwatch—mostly with their consoles—among many other videogames for multiple reasons and with higher preferences for physical and emotional challenges (**OW1**), and those who play Overwatch—mostly with their PC—as one their esports games, with less wide-ranging gaming preferences and a special liking to League of Legends (**OW2**).

Discussion

The goal of this entry chapter was to identify some limited characteristics of Overwatch players and their position in the larger context of esports players. Perhaps the most fundamental of our findings was that the majority of Overwatch players, like many other esports players, tend to like many other videogames too and they also play other esports titles. Based on their self-reported habits, our Overwatch players ended up being clustered into two main groups: those who play Overwatch and Fortnite (**OW1**) and those who play Overwatch and League of Legends (**OW2**). We highlight that 32 individuals in the sample also identified as "pure" Overwatch esports players, and although this amount did not allow us to analyze such type statistically, it is good to keep in mind that—considering the overall number of Overwatch players—those who play Overwatch as their sole esports game may differ from our clusters significantly. To identify these potential differences, larger sample sizes are needed.

Previous research on Overwatch has suggested that its "competitive" discourse is often contrasted with a more general, cultural-product-like reception (Ruotsalainen and Välisalo 2020). Our findings complement and complicate this picture with two large player clusters surfacing from the data—the first of which is oriented toward gaming culture more

generally and widely. It is unlikely that any stereotypical casual/competitive binary would be useful for explaining these two or more types; and indeed, we did not find any esports clusters differing significantly based on such characteristics. Rather, we should acknowledge that some Overwatch players consider the game as a significant part of their overall interest toward gaming and new gaming trends, whereas others may be more specifically committed to Overwatch in particular, in more than one way. In fact, we note that our instruments also asked about the players' gaming motives, preferred game experiences, and competitiveness in particular, and none of the two Overwatch clusters or other clusters differed significantly from each other in this regard. The only difference in experiential play preferences was found to be associated with long-term gaming experiences.

In general, it seems that classifying players into casual and competitive might blind us from a reality where a large part of "casual" players play in order to compete and many "competitive" players, in turn, enjoy the lore and other non-competitive features. Future research could investigate if people's evolving modes of engagement explain player behavior better than any stable "mentality". Regardless of what kind of genres, activity types, and game challenges a player prefers, they may have needs for both "casual" and "competitive" experiences. In line with these more complex scenarios, our data shows that there might be an Overwatch player type preferring physical challenges and emotional interactions, and another type preferring long-term game experiences, both playing other different esports games, too. The below summary of the two Overwatch clusters presents their key characteristics.

OW1: These individuals prefer a wide range of videogames in different genres, and of esports games, they specifically play Fortnite and Overwatch. These players use the console more than any other esports players, and they enjoy various elements in their gaming habits such as caretaking and coordination, and physical as well as socio-emotional challenges.

OW2: These individuals may be more focused on esports, as they play Overwatch and League of Legends in particular. Their key platform is the PC. Whereas the PC is often seen as a more competitive platform with higher accuracy enabled by mice, the players did not report more competitive preferences.

As a major limitation, we must acknowledge that our data did not include objective information regarding the players' actual behaviors (e.g., by in-game tracking), and our survey items did not distinguish between the time of accumulated esports gaming experience. Hence, we cannot draw causal or other inferences between the participants' overlapping experiences of multiple esports games. Also, our methodology did not include qualitative investigations that would have enabled us to better understand how players engage in Overwatch in more detail. Combined with the fact that our sample was not representative of all Overwatch let alone esports players—and the Anglocentric bias in particular—more research is needed to better understand in-depth gaming engagement across different esports games.

Lastly, we note that in both of the above Overwatch clusters half of the players identified as female. Compared to our other esports-specific clusters that were defined by Counter-Strike and Dota 2, this was an exceptionally high percentage and only comparable with Fortnite players. As to gender, our findings thus indicate that Overwatch, with Fortnite, might be a form of esports that many women prefer over other esports. To better understand the players of Overwatch and esports in general, future research should pursue in more detail the patterns of psycholudic development, that is, to what degree players attach to a game like Overwatch, and how their relationship with the game evolves along with their changing lives.

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