Multi-platform Trace Data Reveal Demographic Differences in Video Game Play, but Individuals Vary Far More

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Most knowledge about "who plays (what) video games" comes from surveys subject to recall bias and social desirability effects. Using publicly available behavioral logs from Steam, Xbox, and Nintendo spanning 1.5 million hours from 3768 US and UK adults (18–40 years old), I present a visualization-driven descriptive analysis of how play patterns differ according to age, gender, ethnicity, and neurodiversity. Results uncover a variety of trends that have rarely been observed in public data: among others, that older players' peak playtime occurs approximately 1 hour earlier in the day, that women tend to re-engage with the same game for a longer time period, and that sports games were more popular among Black, Asian, and neurotypical players than among other ethnic groups and neurodiverse players. Despite intriguing group-level trends, however, within-group variation is far larger: demographic characteristics account for at most 5.4% of gameplay behavioral variation. This work provides an empirically grounded complement to survey research and motivates future investigation into the structural and cultural factors shaping play behavior.

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Introduction

Questions about who plays video games and how play varies across demographic groups remain central to games research and practice. Differences in age, gender, ethnicity, and neurodiversity are routinely invoked to explain variation in genre engagement, time investment, social play, and monetization patterns, with implications for theory development, experimental design, and commercial decision-making.

At the same time, many existing claims about demographic differences in play rest on limited empirical foundations, often relying on self-report data, highly aggregated industry statistics (e.g., Entertainment Software Association 2025), and/or homogenous samples (Larrieu et al. 2023). Each of these practices seriously limits our understanding of the true differences in behavior among different groups. Researchers have long known that self-report media use data is often a poor reflection of actual digital behavior (e.g., Parry et al. 2021; Choi et al. 2023; Kahn, Ratan, and Williams 2014).

Demographic characteristics such as age, gender, and culture are used pervasively across games research and practice, but with varying degrees of empirical grounding. In theory, demographic variables are routinely positioned as moderators of core constructs within theories related to impulse purchasing (Zhang et al. 2021), technology acceptance (Harnadi et al. 2025), social influence (Liu 2016), and game preferences (González-González et al. 2022), among others—yet such use often treats demographics as proxies for underlying preferences or motivations without specifying the mechanisms through which they operate. In empirical practice, demographics frequently serve as key predictors of outcomes like player types (Santos et al. 2025), esports participation (Kordyaka et al. 2023), or problematic gaming (Lopez-Fernandez et al. 2019), but the practical significance of these associations is rarely scrutinized (Vornhagen, Tyack, and Mekler 2020; Kirk 1996). In industry and HCI research, demographic segmentation guides decisions about targeting, content, and design for groups such as women and older players (Gerling et al. 2012; Kaufman, Flanagan, and Freedman 2019), though segmentation based on what players' recorded behavior is often recognized as more informative (Norman 2020; Yin, Feng, and Liu 2025). Across all three arenas, the question of how much demographic categories actually explain about individual behavior remains largely unexamined with behavioral data outside of industry internal research.

Digital trace data, defined as behavioral logs automatically collected by digital devices and online platforms, offers a complementary lens. By observing play directly, trace data sidesteps the recall bias and social desirability effects inherent in self-report, while capturing dimensions of play (such as hour-by-hour temporal patterns or engagement span across titles) that surveys cannot feasibly measure. Trace data thus enables more fine-grained descriptions of play and its demographic composition, supports better monitoring of how the characteristics and behaviors of players change over time, and improves predictions about how play and player populations are likely to evolve in the future. The present article marks one such snapshot in the form of a secondary analysis of the Open Play dataset (Ballou et al. 2025)—a large, multi-platform collection of behavioral logs from US and UK adults—to describe how observed play patterns vary across age, gender, ethnicity, and neurodiversity.

In sum, demographic differences are treated as theoretically and practically important, yet the behavioral evidence used to motivate those claims is frequently indirect or coarse. To address this gap, I adopt a descriptive, visualization-first approach that foregrounds both between-group patterns and within-group heterogeneity. I do not conduct null hypothesis significance testing; instead, I focus on the magnitude and structure of observed differences. The work makes two primary contributions:

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- It provides a behaviorally grounded descriptive map of play variation across age, gender, ethnicity, and neurodiversity using observed play histories rather than self-report alone.
- It foregrounds (and quantifies) within-group heterogeneity and distributional overlap, challenging monolithic representations of demographic groups.

Related Work

Who plays games?

Frequent reports, often industry-led, document the changing demographics of people who play games. In the US, players are now almost equally split by gender, are slightly more likely to be white compared to national averages, and 28% are over age 50 (Entertainment Software Association 2025), illustrating the durability of gaming across the lifespan. Among teenagers, the demographics most likely to play are early adolescents (13–14), boys, Black youth, and those from lower-income households (Gottfried and Sidoti 2024). Among US adolescents with mental health difficulties, gaming was relatively popular among Black females and Asian males (Carson et al. 2012).

These contemporary findings contrast with early work characterizing video game players as predominantly male, competitive, and academically high-performing (McClure and Mears 1984; McClure 1985), a portrait that reflected both the demographics of early gaming and the narrow samples used to study them. More recent work has demonstrated the value of large-scale open data for illuminating within- and between-group heterogeneity, as in the case of board game preferences (Cross et al. 2023).

How do demographic characteristics relate to play behavior?

Equally interesting is not who plays games at all, but how, among video game players, subgroups differ. Complementing a large body of work on player types and motivations (Yee 2006; Hughes and Cairns 2020), a range of studies have examined how demographic characteristics relate to specific dimensions of play.

With regard to genre preferences, survey research has found that male gamers are more likely to play Strategy, Role Playing, Action, and Fighting genres, whereas female gamers are more likely to play Social, Puzzle/Card, Music/Dance, and Simulation games (Phan et al. 2012; Tondello and Nacke 2019). Industry data similarly indicate that older players (Gen X and above) gravitate toward ‘Skill & Chance’ games and away from action titles, compared to younger cohorts (Entertainment Software Association 2025). Age, gender, and education level have also been weakly linked to player type archetypes such as “achiever” and “disrupter,” though they appear unrelated to self-reported play frequency (Santos et al. 2025).

Platform choice also varies: teenage boys are more likely to play on console, while smartphones and tablets make up a larger share of teenage girls’ play (Gottfried and Sidoti 2024). Lower socio-economic status has been associated with greater preference for sports games (Andrews 2008).

Studies of neurodiverse players have found a preference for RPGs among adults with autism (Mazurek, Engelhardt, and Clark 2015), as well as higher motivations escapism, completionism, and customisation (Millington, Simmons, and Cleland Woods 2022). Adolescents with ADHD tend to have higher playtime and problematic gaming (Isorna Folgar et al. 2024). However, researchers have criticized the games HCI literature on neurodiversity for being prescriptive or focusing on “cures” rather than understanding the diversity of play experiences and preferences among neurodiverse players, and specifically call for more comparisons between neurotypical and neurodiverse behavioral patterns (Spiel and Gerling 2021).

A smaller number of studies have used behavioral trace data rather than self-report, and their findings sometimes diverge from survey-based accounts. Early analyses of EverQuest II trace data found that playtime did not differ by ethnic background, religious affiliation, or income (Williams, Yee, and Caplan 2008), but that women played approximately 15% more hours per week than men, were more motivated by social factors, and were more likely to under-report their playtime relative to logged data (Williams, Consalvo, et al. 2009). An analysis of League of Legends data showed that women had fewer matches played but accrued skill at the same rate, and were more likely to play support roles (Ratan et al. 2015). Beyond games, analyses of time-use diaries have shown that time spent playing video games is highly sensitive to total available leisure time for younger men, but not for younger women or older men (Aguiar et al. 2017).

Taken together, the existing literature provides a partial but fragmented picture. Most findings derive from single platforms or single games, rely on self-report, or lack demographic diversity. The present study aims to complement this body of work by examining demographic variation in play across multiple platforms using observed behavioral data from a diverse sample, and by quantifying how much heterogeneity in play patterns is accounted for within vs between groups.

Present Study

The present study thus attempts to improve the field’s understanding of demographic differences in play behavior by leveraging the Open Play dataset (Ballou et al. 2025). The Open Play dataset is a publicly available dataset of 3,768 US and UK 18-40 year olds who contributed digital trace data from five gaming platforms (Xbox, Nintendo Switch, Steam, iOS and Android), who were screened using quasi-representative methods (with partial quotas for age, gender, and ethnicity). Analyses are guided by two research questions:

RQ1: How do the volume, composition, and temporal distribution of observed play vary across age, gender, ethnicity, and neurodiversity in this dataset?

RQ2: How much of the total variation in play behavior is attributable to between-group demographic differences versus within-group individual differences?

It is vital to be clear about what the study does not aim to do. Results here should be treated as pattern discovery and fodder for hypothesis generation, rather than population inference. I do not conduct statistical tests, and the present dataset is not fully representative of the general population (who vary tremendously in their propensity to play games) nor of the gaming population (whose demographics remain only loosely understood, and who themselves vary in willingness to participate or share data). Nonetheless, the diversity present in the sample and the breadth of trace data allows for a more detailed look at naturalistic gaming behavior than available in many contemporary studies. Further, the data do not support claims of inherent preferences, or shed light on mechanisms—observed behavioral patterns may reflect structural, cultural, platform-level, or other factors.

Method

The data for this study comprise a subset of the data from the Open Play study (Ballou et al. 2025), version 1.1.0. In that study, participants provided access to automated records of their gaming history on one or more platforms (Xbox, Steam, Nintendo Switch, iOS, Android; Xbox is included for US participants only) and completed an intake survey followed by daily and biweekly surveys. The present study uses only the digital trace data from console and PC and demographic data from the intake survey, and does not include daily or biweekly survey data or mobile data (due to lower granularity compared to other trace data streams). Intake surveys were completed between Sep 2024 and Jan 2026. Digital trace data span the following periods: Nintendo (May 2022 to Oct 2025), Steam (Nov 2024 to Oct 2025), Xbox (Apr 2022 to Sep 2025).

Participants were recruited in collaboration with two panel providers, Prolific and PureProfile. Participants were eligible if they were aged 18 or older, resided in the United States or United Kingdom, self-reported playing video games for at least 1 hour per week with at least 50% of their play happening on eligible platforms (Nintendo, Xbox, and Steam), and successfully linked at least one gaming account on Xbox, Steam, and/or Nintendo Switch with validated recent digital trace data.

The procedure for linking gameplay data differed per platform: Steam was collected through a custom platform developed for research purposes, while Xbox and Nintendo data were collected via non-financial data-sharing agreements with the platform owners. An overview of the procedure from the participant perspective is shown in Appendix Table A1, while full details of the recruitment procedures and study methodology are available in (Ballou et al. 2025).

All data and analysis code are available on [repository link removed for anonymous review; anonymized supplementary materials uploaded to PCS].

Participants

A description of the sample is shown in Table 1.

Participants in the initial screening sample were quasi-representative; quotas ensured that those screened were approximately nationally representative according to age, gender, and ethnicity. However, the analytic sample is non-representative, as both prevalence of gaming (i.e., likelihood of qualifying for the study) and willingness to participate in the intensive study differed across demographic groups in the screening sample. Nonetheless, the analytic sample consists of a diverse sample across gender and ethnicity.

Particularly noteworthy is the neurodiversity of the sample: 23.8% of participants reported having an ADHD diagnosis, and 16.8% of participants reported having an autism spectrum disorder diagnosis (with 7.4% reporting both)—both far above national averages (see e.g., estimates that 6.0% of US adults have ADHD Staley et al. 2024; and 2.2% of US adults have autism Dietz et al. 2020). While such a high prevalence creates challenges for the generalizability of full-sample analyses, having this degree of diversity present in the sample allows for a more nuanced look at how play patterns vary across different neurotypes, rather than treating neurodivergent players as a monolithic group.

Table 1. Participant characteristics by country

Characteristic	Total	US	UK
N	**3768**	**2172**	**1596**
Age (years)	27.1 (5.2)	26.7 (5)	27.5 (5.4)
Gender			
Man	2332 (61.9%)	1298 (59.8%)	1034 (64.8%)
Woman	1233 (32.7%)	740 (34.1%)	493 (30.9%)
Non-binary/ Other	198 (5.3%)	132 (6.1%)	66 (4.1%)
Ethnicity			
White	2679 (71.1%)	1353 (62.3%)	1326 (83.1%)
Asian	323 (8.6%)	188 (8.7%)	135 (8.5%)
Black	250 (6.6%)	212 (9.8%)	38 (2.4%)
Mixed/Multiple	377 (10%)	307 (14.1%)	70 (4.4%)
Other	129 (3.4%)	110 (5.1%)	19 (1.2%)
Neurodiversity			
Neurotypical	2158 (57.3%)	1201 (55.3%)	957 (60%)
ADHD	898 (23.8%)	596 (27.4%)	302 (18.9%)
Autism spectrum	633 (16.8%)	345 (15.9%)	288 (18%)
Platform			
Nintendo	1442 (38.3%)	789 (36.3%)	653 (40.9%)
Steam	2805 (74.4%)	1577 (72.6%)	1228 (76.9%)
Xbox	326 (8.7%)	326 (15%)	0 (0.0%)

Values are M (SD) or N (percent). Neurodiversity categories are non-exclusive.

Measures

Demographic variables

The following demographic variables were measured in the intake survey.

Age: Participants entered their age as an integer. Because the multivariate visualizations used here (e.g., radar charts comparing genre profiles) require categorical groupings, continuous age is binned into four groups (18–24, 25–30, 31–35, 36–40) for comparability with the other demographic dimensions.

Gender: Participants selected from the following options: Woman, Man, Non-binary, Prefer to specify, and Prefer not to say. For simplicity, “non-binary” and “prefer to specify” were recoded as “Non-binary/other”.

Ethnicity: Response options were drawn from primary census categories in each respective country. US participants selected between White alone; Black or African American alone; American Indian and Alaska Native alone; Asian alone; Native Hawaiian and Other Pacific Islander alone; Some Other Race alone; and Two or More Races. UK participants selected among White; Mixed or multiple ethnic groups; Asian or Asian British; Black, African, Caribbean or Black British; Other ethnic group; Prefer not to say. For simplicity, I harmonized these categories into a smaller set of labels (e.g., “Black or African American alone” and “Black, African, Caribbean or Black British” were both recoded as “Black”).

Neurodiversity: Participants were asked if they had received a formal diagnosis of neurodiverse conditions from a qualified healthcare professional; if they selected yes, they were provided a list of 12 options. In this paper, I focus solely on players who reported having a diagnosis of either autism spectrum disorder or attention deficit hyperactive disorder, as prevalence of other categories (e.g., dyscalculia) was too small for meaningful analysis.

Gaming behavior variables

Gaming behavior on Xbox, Steam, and Nintendo Switch was measured via a mix of (a) session-level data provided by Nintendo of America, Nintendo of Europe, and Microsoft; and (b) hourly playtime collected using open source methods built on the Steam API. The exact data-sharing procedure and data collected varied by platform; details are available in Appendix Table A1, and are described in exhaustive detail in Ballou et al. (2025).

Because Xbox titles are replaced with a random identifier instead of the specific game, subsequent analyses in this paper do not focus on particular games, but rather on genres (as this metadata was provided alongside Xbox games). For reference, the most popular 5 non-Xbox games for each demographic group are shown in Table A2

From the hourly and session-level data, I calculated various summary variables including: total playtime (hours), session count, mean session duration, genre categories (how assigned to titles), title diversity, and hour of day and day of week distributions. These derived variables form the basis of the descriptions to come.

Genres

Nintendo and Steam data contain full game titles; to collect game metadata including genres, we used the Internet Games Database (IGDB) API. Xbox data was provided using random identifiers in place of game titles, but with genre labels as seen on the Xbox store. For simplicity, I therefore harmonized IGDB and Xbox genres into a smaller subset of categories (e.g., turn-based strategy, real-time strategy, tactical, MOBA were collapsed into a single “Strategy” category). Full details of the genre mapping are available in the supplementary materials. For the primary genre analysis, each game was assigned to its first listed genre, typically the primary genre; a supplementary multi-genre analysis (Appendix Figure A1) apportioned playtime equally across all genres a game was tagged with and largely replicated the findings.

Ethics

This study received ethical approval from [redacted for anonymous peer review]. All participants provided informed consent at the start of the study, including consent to their data being shared openly for reanalysis.

Participants were paid at an average rate of £12/hour, equating to: £0.20 for a 1-minute screening, £2 for the 10-minute intake survey (plus £5 for linking at least one account with recent data), £0.80 for each 4-minute daily survey. Participants received a £10 bonus payment for completing at least 24 out of 30 daily surveys.

Results

Results below first depict the behavioral patterns observed in play volume, engagement patterns and temporal organization, and genre composition, before quantifying total explanatory power.

Play volume across demographic groups

Figure 1 visualizes the typical weekly playtime (Panel A, top row), total recorded sessions (Panel B, middle row), and typical session duration (Panel C, bottom row) for each group. The heavily overlapping histograms across groups indicate that group differences account for very little variation in playtime: in the sample, most groups showed similar distributions of play volume.

A few trends nonetheless emerge: women played fewer weekly hours than men (5.2 vs 8.1 mean hours). There is a small observed difference in the total number of sessions played by participants with ADHD compared to neurotypical players (169 vs 128), but no difference in median session duration (31 vs 31 minutes). Asian players in the sample had slightly lower playtime and sessions than other ethnic groups.

Figure 2 shows difference in engagement tendencies, with engagement span (i.e., the median time between the first and last recorded session of a game, for games with recorded sessions on at least 2 separate days) on the x-axis, and median hours played per distinct game on the y-axis. The upper left represents groups that spend more time in a typical game and concentrate this time into a shorter period, whereas the bottom right represents groups

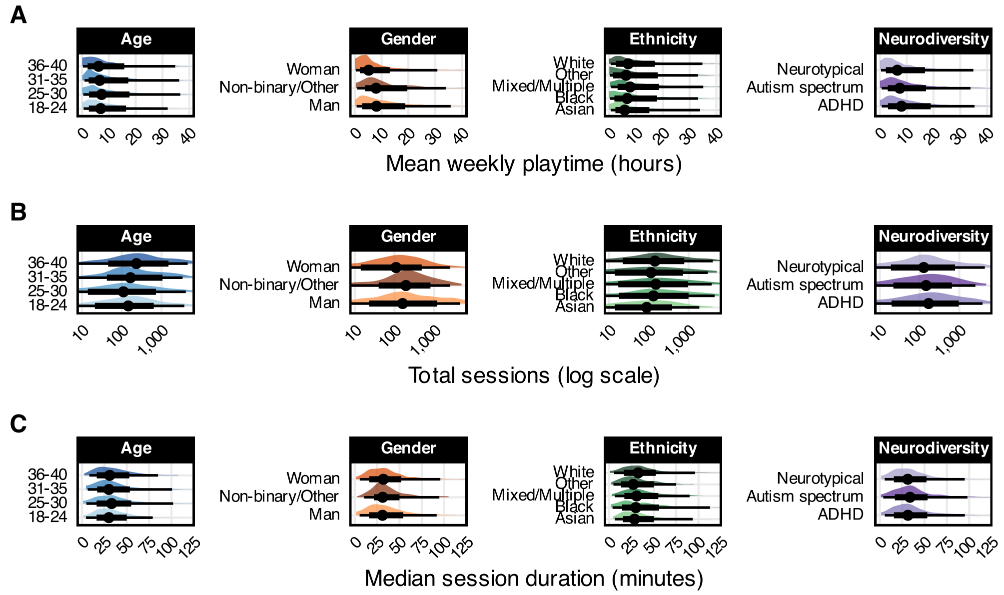

Figure 1. Distribution of play volume metrics across demographic groups. (A) Mean weekly playtime in hours. (B) Total session count (Nintendo + Xbox only; log scale). (C) Median session duration in minutes. Density slabs show the distribution shape; points and intervals show the median and 66%/95% quantile intervals. Distributions show substantial overlap across groups.

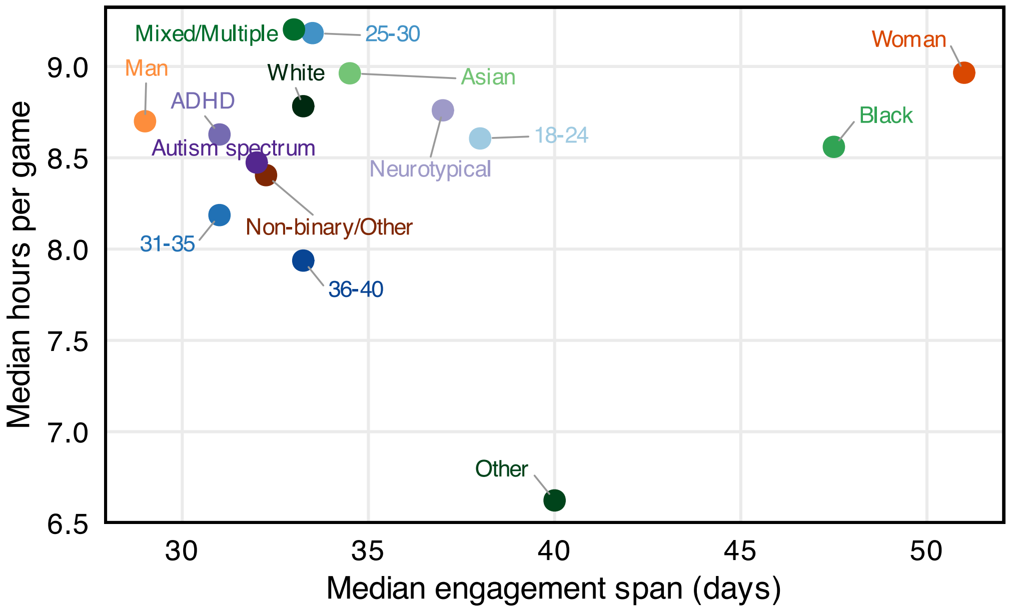

Figure 2. Game-level engagement across demographic groups: median hours invested per sticky game (played on 2+ days) vs. median calendar span of engagement. Colors indicate demographic dimensions: blues = age, oranges = gender, greens = ethnicity, purples = neurodiversity.

that play less of a particular game, and spread this time out over a longer period.

Results show only small differences in engagement time, with most groups playing between 7.9 and 9.2 hours before moving onto another game. Black and women players tend to spread their engagement out over a longer period, with a typical game being played for approximately 50 days, whereas men and most other groups tend to play a game between 29 and 40 days.

Temporal patterns across demographic groups

Next, I assessed how the time of play differs across demographic groups in the sample. For each user, I calculated the proportion of total playtime taking place in each of 24

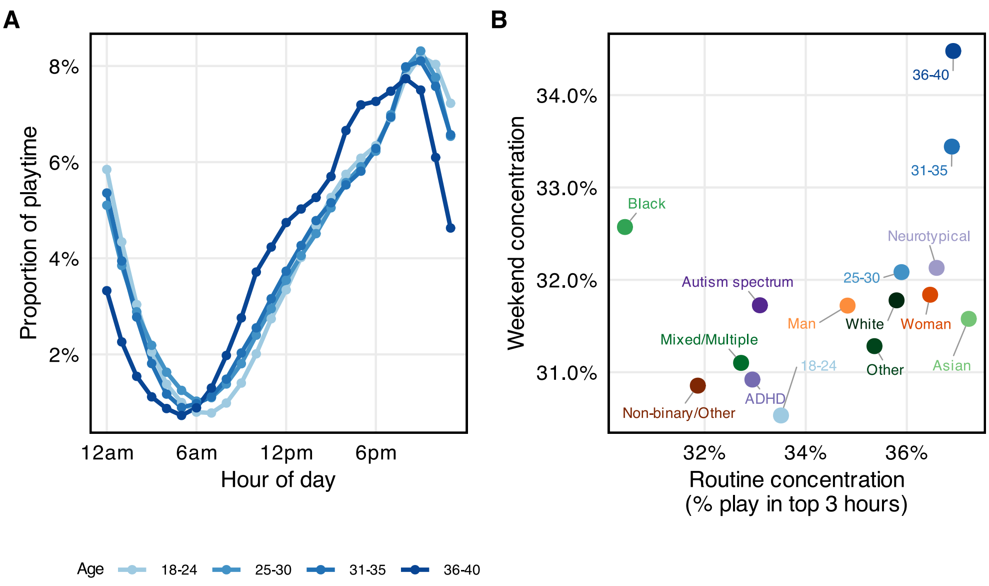

Figure 3. Temporal patterns of play across demographic groups. (A) Distribution of play across hours of the day by age group; lines show the proportion of each group's total playtime in each hour. (B) Routine concentration (% of playtime in top 3 hours; higher = more consistent schedule) vs. weekend concentration across all demographic groups.

hourly bins, after converting session timestamps to local timezones. I further calculated the proportion of playtime taking place on weekdays vs weekends, and the percentage of play that takes place during a given person's top 3 hours. The latter constitutes an index of play routine and stability (for example, someone plays exclusively between 6–9pm would have a value of 100%, whereas someone who plays equally throughout the 24-hour would have a value of 3/24 = 12.5%).

Results (Figure 3, Panel A) show that 18–35 year olds have similar play patterns, with 9pm being the peak gaming hour. Playtime among 36-40 year-olds shifts slightly earlier, peaking at 8pm.

Figure 3 Panel B shows routine and weekend concentration for each demographic group. In the present sample, older players concentrated their play on weekends more than younger groups (30.5% of play taking place on weekends for 18–24 year olds vs 34.5% for 36–40 year olds) and had more fixed routines (33.5% of 18–24 year olds' play took place within their top 3 hours, compared to 36.9% for 36–40 year olds). Among ethnic backgrounds, Asian players had the most stable play routines, whereas Black players were least concentrated in consistent times of day (30.4% of playtime falling in the top 3 hours for Black players, 37.2% for Asian players).

Genre composition across demographic groups

To visualize differences in genre preferences, I calculated the sum of each user's playtime taking place in each of the 8 genres within the simplified genre taxonomy described in the measure section (raw play proportions for all 23 genres in the unsimplified data can be found in Appendix Table A3).

Results (Figure 4) visualizes these results. Each demographic group is a radar; the grey circle represents average genre allocation for all other groups (i.e., for 18-24 year olds, the grey line represents the average genre allocation across all age groups, 25–40). The outer dashed line represents 200% of that average, and the inner dashed ring represents 50%. Points farther from the center therefore indicate that this genre is relatively popular among that demographic group, whereas points closer to the center indicate that the genre is relatively unpopular.

A wide variety of observed differences emerge. Among other differences, results in the present sample align with well-documented preferences among men for sports games, and among women for puzzle and simulation games. Asian players in the sample played relatively high amounts of racing, platform, and sports games, whereas White players played slightly more puzzle games than other ethnic groups. Neurodiverse players had slight preference for RPGs compared to neurotypical players, who played more racing games.

Intersectional genre patterns

Figure 4 examines each demographic dimension in isolation, but players simultaneously occupy multiple demographic categories. Figure 5 presents a heatmap investigating potential intersectional trends using the same leave-one-out methodology as the radar charts, whereby each cell shows how an intersection's genre proportion compares to everyone not in that intersection.

Results indicate that several of the genre trends observed in Figure 4 may be driven by intersectional trends. For example, the preference among women for puzzle games was particularly strong among 25–30 White woman, both neurodiverse and neurotypical, while the preference for strategy games was strongest in the

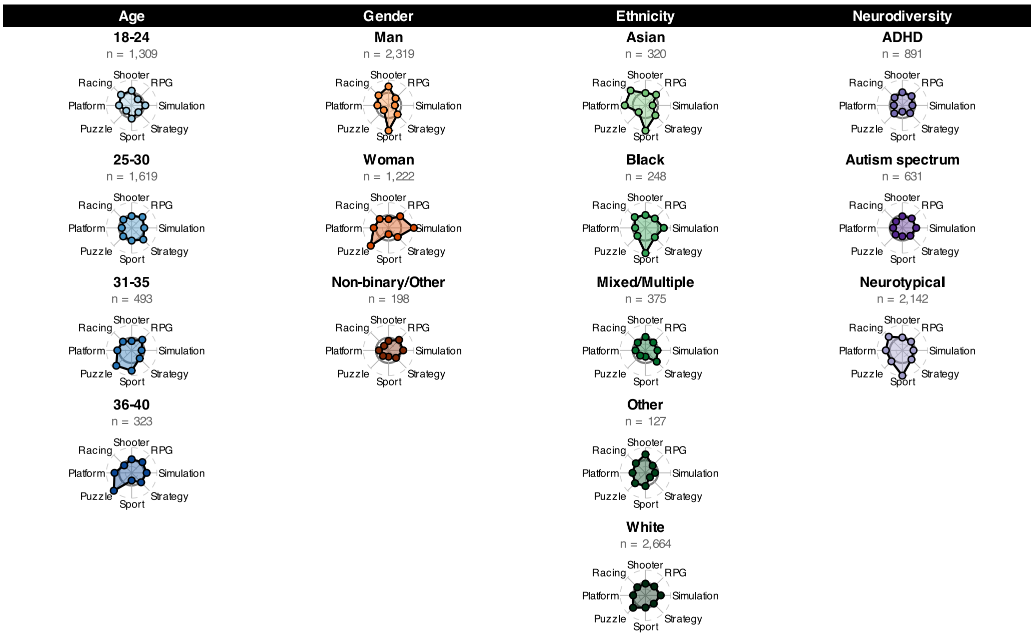

Figure 4. Genre playtime profiles across demographic groups (primary genre only). Each radar shows deviation from all other groups in that demographic dimension: the grey circle represents median genre allocation for all other groups, the outer dashed line represents 200% of that median, and the inner dashed ring represents 50%.

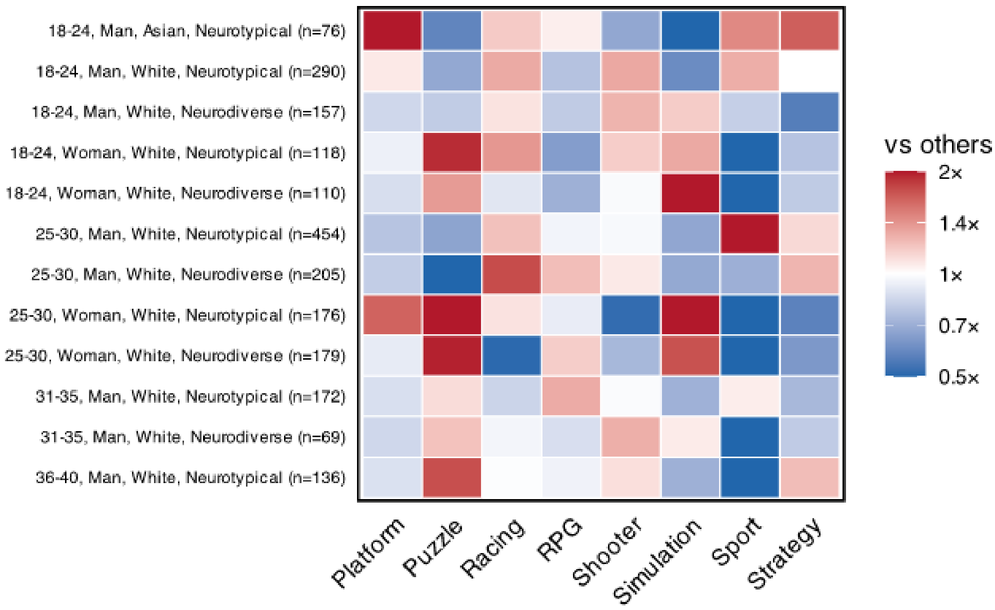

Figure 5. Genre preference profiles across intersectional demographic groups. Each cell shows the ratio of genre playtime in that intersection compared to all other participants (leave-one-out). Red indicates over-representation, blue indicates under-representation. Only intersections with n ≥ 60 participants are shown.

18-24 neurotypical Asian men group. Intersectional results should be interpreted with caution, due to the smaller sample sizes within each intersection and the inherent idiosyncrasies of the full sample.

Variance decomposition

The preceding analyses reveal differences in central tendency across demographic groups, but these visualizations can obscure how much of the total variation in play behavior lies between groups versus within groups. If between-group variance is small relative to within-group variance, demographic categories explain little of the overall heterogeneity in how people play—even if group means differ noticeably.

To quantify how much of the variation in play behavior is attributable to demographic categories versus individual differences, I calculated the proportion of total variance in an outcome that lies between groups rather than within groups, computed as `SS_between / SS_total`. For the combined estimate, I fit a multiple linear regression predicting each outcome from all four demographic variables simultaneously (age group, gender, ethnicity, and neurodiversity) and extracted R^2, which represents the total variance explained by the full demographic profile. Values near zero indicate that demographic categories explain little of the overall heterogeneity in play behavior, even when group means differ noticeably.

Table 2. Proportion of variance explained by demographic categories (eta-squared). Values represent the percentage of total variance in each outcome attributable to between-group differences.

Outcome	Age	Gender	Ethnicity	Neuro	Combined (main effects)	Combined (full)
Volume						
Session count	0.6%	2.5%	0.4%	0.0%	3.2%	5.4%
Session duration	0.5%	0.0%	0.3%	0.0%	0.9%	4.6%
Weekly hours	0.1%	2.7%	0.3%	0.2%	3.5%	5.0%
Composition						
Genre diversity	0.2%	0.8%	0.5%	0.6%	2.2%	3.4%
Genres played	0.4%	1.2%	0.6%	1.1%	3.3%	4.8%
Temporal						
Routine concentration	0.8%	0.5%	0.7%	1.1%	3.2%	5.1%
Weekend concentration	0.7%	0.1%	0.0%	0.1%	0.8%	2.5%

Combined (main effects) = R^2 from multiple regression with separate, linear and simultaneous demographic predictors. Combined (full) = R^2 with splines on age and all two-way interactions. Neuro = Neurodiversity (Neurotypical vs. ADHD/autism).

Results in Table 2 show that across all outcomes and demographic dimensions, the vast majority of variance in play behavior is within-group rather than between-group. Demographic categories explain less than 3% of total variance in every case, with most values below 1%. Even in a more parameterized specification with flexible age effects and all two-way interactions, the maximum variance explained was 5.4%.

In short, individuals within the same demographic group differ from one another far more than group averages differ from each other. This pattern holds across volume, composition, and temporal outcomes, reinforcing that demographic labels capture only a small slice of the heterogeneity in how people play.

Discussion

The results presented here show a variety of trends among demographic groups in a diverse sample of UK and US adult video game players. Many these have been documented in prior survey-based research, such as the prevalence of sports game play among men and simulation game play among women (Phan et al. 2012) or the preference for RPGs among adults with autism (Mazurek, Engelhardt, and Clark 2015). Other patterns are intuitive and have been theorized, but rarely directly observed and quantified in naturalistic behavioral data, such as the 1 hour earlier peak time and higher weekend concentration for older players (Ream, Elliott, and Dunlap 2013).

However, despite the presence of these trends, the overall picture is one of substantial heterogeneity within groups, and thus overlap between them. For every observed difference, there are many individuals in the "opposite" group who show the same behavior. For example, although there is a marked difference in the average proportion of time men and women in the sample spent playing games in the shooter genre (33% vs 24.4% on average), there are still 208 (17%) women who have a higher shooter proportion than the average man. Results showing that effectively all permutations of play volume, timing and genre allocation are present in all demographic groups serves as a form of counter-stereotypical examples, a method recommended for reducing and reversing implicit biases in games culture (Flanagan and Kaufman 2017).

In other words: while trends emerge at a bird's eye view, knowing an individual's complete demographic profile tells us remarkably little about their actual play behavior. Even with all demographic variables combined, a researcher could explain at most 5.4% of the variance in any single play outcome (Table 2). These findings echo early trace data studies showing demographic categories explain minimal variance in play patterns (Williams, Yee, and Caplan 2008), but extend them to contemporary multi-platform contexts and provide explicit variance decomposition.

It is vital to interpret these results with care, and to avoid overgeneralization or stereotyping. The observed differences do not necessarily reflect stable preferences or inherent traits of demographic groups, but rather patterns of behavior that emerge from a complex interplay of structural factors, cultural contexts, and individual circumstances. For example, differences in temporal play patterns may reflect differences in work schedules (e.g., Lee and Chen 2023), caregiving responsibilities (e.g., Wang, Taylor, and Sun 2018), accessibility concerns (Porter and Kientz 2013), or availability of gaming platforms (e.g., Ha and Kim 2024), rather than intrinsic preferences for when to play. Similarly, genre preferences may be shaped by factors such as marketing, social norms, or peer influence, rather than inherent tastes. For example, it is long-established that White adult male characters are over-represented among video game characters, while Black female characters and many other groups are under-represented (Williams, Martins, et al. 2009; Jones et al. 2025; cf. Gardner and Tanenbaum 2018), which may contribute to the observed differences in genre allocation.

With those caveats in mind, this work still offers several contributions for the field: it offers a foundation for hypothesis generation, theory specification, and study design; highlights behavioral dimensions such as routine concentration or genre diversity that may be more informative outcomes than total playtime; and points to the value of behavioral trace data in revealing how people actually play, rather than what they say about their play.

Implications for the Use of Demographic Variables

These findings complicate how demographic categories should function in games HCI theory. When within-group variance is at least 18x larger than between-group variance, demographics may be valuable as contextual background variables but are unlikely to be useful as primary predictors of behavioral outcomes. Such empirical backing reinforces known challenges for theory, quantitative methods, and design.

On the theory side, I argue for improved specification of the specific *mechanisms* through which demographics matter rather than treating them as proxies for preferences. Although there is widespread recognition of the pitfalls of demographic essentialism at the theory level, empirical studies often use and interpret demographics are key predictors of outcomes such as motivational styles or player types (Yee 2006), esports participation (Kordyaka et al. 2023), or internet gaming disorder (Lopez-Fernandez et al. 2019). Such use of demographic variables may serve as a proxy for preferences or behaviors, masking the underlying mechanistic differences on which the field could actually intervene. Future work with representative samples and/or qualitative methods can help unpack which of these trends generalize to other metrics of real-world play, and why they occur (access? cultural exposure? time constraints?).

Eventually, such work may allow mechanism-related variables to supplement demographics themselves in quantitative studies. Results here show that the use of demographics variables in statistical models should be carefully considered. Researchers should report and be mindful of effect sizes, and ensure that statistical significance of a particular demographic variable is not conflated with the practical significance thereof (Kirk 1996; Vornhagen, Tyack, and Mekler 2020).

With regard to design, these results suggest that demographic categories may be useful for coarse segmentation, but heterogeneity will often be too large to reliably base more granular decisions such as design for diverse groups such as women or older players (Gerling et al. 2012; Kaufman, Flanagan, and Freedman 2019). Behavioral segmentation based on characteristics like genre allocation and temporal play patterns, a well-established industry practice (Yin, Feng, and Liu 2025; Norman 2020), offers a valuable alternative for many design or intervention decisions.

To reiterate, low predictive strength does not mean demographics have no value for design or analytics. Observed differences in temporal organization and engagement span suggest that features such as session length expectations, save mechanics, or live-service timing may differentially fit players with distinct demographic constraints (Figure 3). Similarly, genre portfolio patterns can inform decisions about cross-promotion, onboarding pathways, and content diversification strategies.

Limitations, Generalizability, and Future Directions

As highlighted throughout this piece, these data do not provide strong evidence for generalizable differences between groups. I did not apply weighting or conduct hypothesis tests. Observed differences should not be interpreted as stable preferences or group traits, as these data cannot meaningfully distinguish access effects from preference effects.

The gameplay behavior observed here is wide but shallow - while the data captured individuals' play across a wide variety of titles (mean: 19.6 distinct titles per player), it does not capture their behavior within particular games. To advance knowledge on various topics typically studied using self-reports or in lab settings, deep game-level is needed instead: for example, avatar selection data to study the Proteus Effect (Yee and Bailenson 2007), performance data to study skill acquisition (Ratan et al. 2015), and communications and friends data to understand gender differences in social behavior (Wilhelm 2018). Achieving such advances will require more widespread adoption of the full trace data collection toolkit, ranging from data donation (which has already proven successful for behavioral research on social media, e.g., Yap et al. 2024; Es and Nguyen 2025), scraping-based methods (Ballou et al. 2024), and existing APIs (e.g., Vuorre et al. 2021; although see Davidson et al. 2023 for transparency issues associated with platform-provided APIs).

Further, while the quasi-representative sampling strategy underlying this data produced a sample more diverse than many comparable studies of video game trace data (e.g., Ballou et al. 2024; Larrieu et al. 2023), the sample here is not random or representative of either the general population or of all video game players. Such trade-offs are inherent: with the exception of extremely rare studies that have access to population data via platform owners (e.g., Zendle et al. 2023), collecting demographic data requires contacting individual participants who may elect not to join the study. Selection biases are thus present with regard to willingness to share data, sufficient gaming on included platforms, and participation in the survey platforms from which recruitment took place (Prolific, PureProfile).

I particularly draw attention to the exclusion of mobile gaming due to insufficient data granularity, as previous results have shown that the demographics of mobile players systematically differ from those of other gaming platforms (Entertainment Software Association 2025; Gottfried and Sidoti 2024). Similarly, the lack of Xbox data among UK participants means recorded behavior and game composition differs across countries ; to mitigate this, the analyses intentionally do not compare the US and UK, but group all participants. The combination of selection biases present in the study also likely contributed to some of the surprising characteristics of the sample, such as high self-reported rates of neurodiversity.

In short, more representative or targeted samples, deep game-level data, and qualitative follow-up are all needed to build on this work. Future research should aim to disentangle access effects from preference effects, assess the generalizability of these patterns, and further unpack the lived experiences underlying observed demographic differences.

Conclusion

This study used publicly available behavioral trace data from Steam, Xbox, and Nintendo Switch to describe how play patterns vary across age, gender, ethnicity, and neurodiversity in a diverse sample of 3,768 US and UK adults. Results revealed a range of demographic differences in play volume, temporal organization, engagement span, and genre composition, many of which corroborate prior survey-based findings, while others (such as the earlier peak playtime among older players or the longer engagement spans among women and Black players) have rarely been directly observed in naturalistic data.

Yet the overarching finding is one of within-group heterogeneity: demographic characteristics collectively explained less than 6% of the variance in any dimension of play behavior examined. These results suggest that while demographic categories remain useful for coarse description and hypothesis generation, they are poor proxies for how any individual actually plays. Future work should aim to move beyond demographics as default predictors, instead investigating the structural, cultural, and individual-level mechanisms that give rise to the patterns observed here, and doing so with representative samples, deep game-level data, and methods that center players' own accounts of their play.

Data Availability

[Redacted for anonymous peer review]

Funding

[Redacted for anonymous peer review]

Disclosures

A portion of the data in this study (Xbox and Nintendo Switch trace data) was collected via data-sharing agreements with Microsoft, Nintendo of America, and Nintendo of Europe. Industry partners did not contribute funding for the research or any of the researchers involved in conducting it, and had no role in the design, analysis, or publication of results.

The author declares no other potential financial, intellectual, or institutional conflicts of interests.

Generative AI

Claude Code (claude-opus-4-5-20251101) was used to prepare and document analysis code. The author takes full responsibility for the content of the analyses and any errors that may be present.

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References

Appendix

Table A1. Platform details.

Platform	Source	Account Linking	Data Type
Nintendo	Nintendo of America/Europe data-sharing	Participants share QR code identifier from Nintendo web interface; Nintendo retrieves and shares gameplay data	Session records (game, time, duration) for first-party Nintendo games only
Xbox (US only)	Microsoft data-sharing	Participants opt in via Xbox Insiders; Microsoft shares pseudonymized data	Session records with anonymized titles; genre and age rating preserved
Steam	Custom web app (Gameplay.Science)	Participants authenticate via Steam API (OpenID); gameplay monitored for study duration	Hourly aggregates per game.
iOS	iOS Screen Time screenshots	Screenshots of up to 3 weeks of gaming; data extracted via OCR	Daily aggregates
Android	Digital Wellbeing screenshots	Screenshots of up to 3 weeks of gaming; data extracted via OCR	Daily aggregates

Nintendo-published games accounted for 63 percent of Switch playtime in the sample.

Table A2. Top 5 games by total playtime for each demographic group (Nintendo and Steam only; Xbox titles excluded due to de-identification).

Demographic	Group	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Age	18-24	Animal Crossing New Horizons (14,080h)	Marvel Rivals (10,507h)	The Legend of Zelda Tears of the Kingdom (8,281h)	Counter-Strike 2 (6,519h)	Splatoon 3 (6,194h)
Age	25-30	Animal Crossing New Horizons (16,075h)	Pokemon Scarlet / Violet (11,369h)	The Legend of Zelda Tears of the Kingdom (11,129h)	Marvel Rivals (8,187h)	Counter-Strike 2 (6,566h)
Age	31-35	The Legend of Zelda Tears of the Kingdom (5,047h)	Pokemon Scarlet / Violet (2,857h)	Animal Crossing New Horizons (2,814h)	FINAL FANTASY XIV Online (2,136h)	Football Manager 2024 (1,664h)
Age	36-40	The Legend of Zelda Tears of the Kingdom (3,128h)	Animal Crossing New Horizons (3,061h)	Pokemon Scarlet / Violet (2,870h)	Mario Kart 8 Deluxe (1,253h)	Football Manager 2024 (959h)
Ethnicity	Asian	Marvel Rivals (1,758h)	Umamusume: Pretty Derby (1,748h)	MapleStory (1,710h)	The Legend of Zelda Tears of the Kingdom (1,560h)	Pokemon Scarlet / Violet (1,508h)
Ethnicity	Black	Animal Crossing New Horizons (2,710h)	Marvel Rivals (2,047h)	Super Smash Bros Ultimate (1,697h)	Splatoon 3 (1,621h)	The Legend of Zelda Tears of the Kingdom (1,532h)
Ethnicity	Mixed/Multiple	Marvel Rivals (3,876h)	Animal Crossing New Horizons (2,723h)	FINAL FANTASY XIV Online (2,277h)	Pokemon Scarlet / Violet (1,918h)	The Legend of Zelda Tears of the Kingdom (1,660h)
Ethnicity	Other	Pokemon UNITE (1,399h)	Super Smash Bros Ultimate (1,069h)	Marvel Rivals (711h)	Umamusume: Pretty Derby (698h)	The Legend of Zelda Tears of the Kingdom (584h)
Ethnicity	White	Animal Crossing New Horizons (28,694h)	The Legend of Zelda Tears of the Kingdom (22,238h)	Pokemon Scarlet / Violet (16,978h)	Marvel Rivals (11,847h)	Counter-Strike 2 (10,766h)
Gender	Man	Pokemon Scarlet / Violet (13,868h)	The Legend of Zelda Tears of the Kingdom (13,449h)	Counter-Strike 2 (12,824h)	Marvel Rivals (12,164h)	Animal Crossing New Horizons (7,842h)
Gender	Non-binary/Other	Animal Crossing New Horizons (4,157h)	Baldur's Gate 3 (2,361h)	The Legend of Zelda Tears of the Kingdom (2,155h)	Warframe (1,973h)	Splatoon 3 (1,442h)
Gender	Woman	Animal Crossing New Horizons (23,987h)	The Legend of Zelda Tears of the Kingdom (11,980h)	Marvel Rivals (6,713h)	Pokemon Scarlet / Violet (6,417h)	Splatoon 3 (5,736h)
Neurodiversity	ADHD	Animal Crossing New Horizons (12,890h)	The Legend of Zelda Tears of the Kingdom (7,363h)	Marvel Rivals (6,823h)	Pokemon Scarlet / Violet (5,170h)	Baldur's Gate 3 (4,804h)
Neurodiversity	Autism spectrum	Animal Crossing New Horizons (8,301h)	The Legend of Zelda Tears of the Kingdom (6,134h)	Pokemon Scarlet / Violet (5,172h)	Splatoon 3 (4,536h)	Baldur's Gate 3 (4,077h)
Neurodiversity	Neurotypical	The Legend of Zelda Tears of the Kingdom (14,973h)	Animal Crossing New Horizons (14,348h)	Pokemon Scarlet / Violet (11,657h)	Marvel Rivals (10,916h)	Counter-Strike 2 (10,309h)

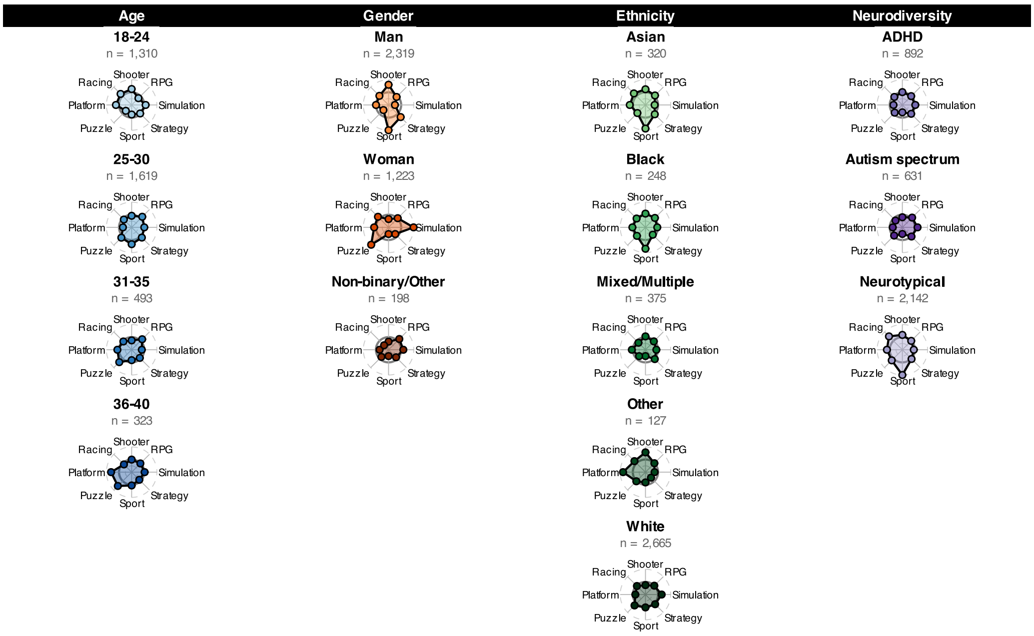

Figure A1. Genre playtime profiles across demographic groups (all genres). Games contribute playtime to all genres they are tagged with, not just the primary genre. Each radar shows deviation from median genre allocation across all other groups in that demographic dimension.

Table A3. Median individual genre allocation by raw genre categories across demographic groups. Values show median percentage of each player's playtime allocated to each genre. The 'Radar' column shows the simplified category used in radar charts (— if not included).

Genre	Radar	18-24	25-30	31-35	36-40	Man	NB/Ot	Woman	Asian	Black	Mixed	Other	White	Neuro	ADHD	Autis
Adventure	—	14.8	17.3	20.0	20.3	16.5	15.7	18.1	17.4	16.4	15.1	14.3	17.5	17.5	15.2	16.4
Role-playing (RPG)	RPG	11.1	14.5	15.4	14.0	12.7	15.0	13.1	13.2	13.5	12.5	13.6	13.1	13.1	13.3	14.4
Shooter	Shooter	15.3	12.5	9.9	13.4	14.4	8.7	9.5	16.0	14.6	14.2	20.0	12.2	13.9	13.0	11.0
Simulator	Simulation	11.4	10.7	8.5	11.1	8.3	12.2	17.2	8.6	10.4	9.6	7.5	11.3	10.4	10.7	12.3
Indie	—	9.9	10.0	9.3	10.6	9.1	12.4	12.0	10.5	8.6	11.0	6.9	9.9	9.3	10.0	10.1
Strategy	Strategy	6.2	8.0	7.4	6.5	7.3	5.4	7.2	6.4	5.4	7.8	4.2	7.4	7.3	6.5	7.7
Platform	Platform	3.2	2.4	3.3	4.5	2.8	1.7	3.3	3.2	3.1	2.6	4.2	2.7	3.1	2.1	2.2
Sport	Sport	2.0	2.9	2.2	2.7	3.0	1.0	1.5	4.4	4.4	1.2	2.2	2.4	3.2	1.6	1.4
Puzzle	Puzzle	1.9	2.1	2.9	3.8	1.8	1.8	3.6	1.6	1.8	1.5	3.2	2.3	2.5	1.8	2.0
Tactical	Strategy	3.1	2.4	2.4	2.2	3.1	0.9	1.7	3.3	1.6	1.6	1.7	2.8	3.1	2.0	2.2
Racing	Racing	2.5	1.9	1.8	1.9	2.0	0.9	2.4	2.9	2.3	1.7	2.8	2.1	2.6	1.8	1.7
Turn-based strategy (TBS)	Strategy	1.7	2.0	2.2	3.2	1.9	1.7	2.2	2.9	2.1	1.2	1.9	2.0	2.2	1.7	1.9
Real Time Strategy (RTS)	Strategy	1.2	2.4	1.8	2.3	2.1	1.8	1.3	2.8	1.2	2.2	2.7	1.7	2.3	1.4	1.7
Card and Board Game	Puzzle	1.2	1.9	2.3	2.6	1.3	1.0	3.2	2.4	1.9	1.7	1.4	1.6	2.2	1.3	1.3
Arcade	—	2.0	1.3	1.4	1.6	1.4	0.9	2.1	2.3	2.5	1.1	3.3	1.5	1.7	1.3	1.4
Hack and slash/ Beat 'em up	—	1.2	1.5	1.5	1.3	1.5	1.2	1.0	2.4	1.3	1.6	1.5	1.3	1.5	1.0	1.2
Visual Novel	—	1.0	0.9	1.4	1.3	0.8	1.5	1.2	1.8	2.7	1.2	1.4	0.7	1.1	0.9	0.8
Fighting	—	1.0	0.8	0.9	1.1	1.1	0.6	0.7	1.3	1.9	1.5	1.5	0.8	1.0	0.8	0.6
MOBA	Strategy	0.7	1.2	2.1	0.9	1.1	0.5	0.8	0.7	0.8	0.7	1.1	1.1	1.0	1.2	0.8
Music	—	0.7	0.5	1.0	1.0	0.5	1.0	0.7	1.4	0.6	0.6	0.3	0.5	0.5	0.7	0.8
Point-and-click	—	0.4	0.5	0.7	0.4	0.3	0.7	0.7	0.2	3.0	0.7	0.1	0.5	0.5	0.4	0.5
Quiz/ Trivia	Puzzle	0.2	0.1	0.3	0.7	0.2	0.4	0.1	0.1	0.2	0.1	0.1	0.2	0.2	0.2	0.4
Pinball	—	0.2	0.1	0.4	0.0	0.2	0.0	0.0	0.0	0.9	0.0	0.2	0.1	0.2	0.0	0.1

Values are median percentages of individual players' genre allocations (matching radar chart methodology). 'Radar' shows the simplified category used in the main text radar plot (— if genre is not included in the 8 simplified categories). Neuro = Neurotypical, Autis = Autism spectrum.

Aguiar, Mark, Mark Bils, Kerwin Kofi Charles, and Erik Hurst. 2017. "Leisure Luxuries and the Labor Supply of Young Men." w23552. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w23552.

Andrews, Gillian 'Gus'. 2008. "Gameplay, Gender, and Socioeconomic Status in Two American High Schools." *E-Learning and Digital Media* 5 (2): 199–213. https://doi.org/10.2304/elea.2008.5.2.199.

Ballou, Nick, Tamás Andrei Földes, Matti Vuorre, Thomas Hakman, Kristoffer Magnusson, and Andrew K Przybylski. 2025. "Open Play: A Longitudinal Dataset of Multi-Platform Video Game Digital Trace Data and Psychological Measures." PsyArXiv. https://doi.org/10.31234/osf.io/nz96c_v1.

Ballou, Nick, Craig Jeffrey Robb Sewall, Jack Ratcliffe, David Zendle, Laurissa Tokarchuk, and Sebastian Deterding. 2024. "Registered Report Evidence Suggests No Relationship Between Objectively-Tracked Video Game Playtime and Wellbeing over 3 Months." *Technology, Mind, and Behavior* 5 (1): 1–15. https://doi.org/10.1037/tmb0000124.

Carson, Nicholas, Benjamin Lê Cook, Chih-Nan Chen, and Margarita Alegria. 2012. "Racial/Ethnic Differences in Video Game and Internet Use Among US Adolescents with Mental Health and Educational Difficulties." *Journal of Children and Media* 6 (4): 450–68. https://doi.org/10.1080/17482798.2012.724592.

Choi, Heeryung, Philip H. Winne, Christopher Brooks, Warren Li, and Kerby Shedden. 2023. "Logs or Self-Reports? Misalignment Between Behavioral Trace Data and Surveys When Modeling Learner Achievement Goal Orientation."

In *LAK23: 13th International Learning Analytics and Knowledge Conference*, 11–21. Arlington TX USA: ACM. https://doi.org/10.1145/3576050.3576052.

Cross, Liam, Andrea Piovesan, Micael Sousa, Peter Wright, and Gray Atherton. 2023. "Your Move: An Open Access Dataset of over 1500 Board Gamer's Demographics, Preferences and Motivations." *Simulation & Gaming* 54 (5): 554–75. https://doi.org/10.1177/10468781231189493.

Davidson, Brittany I., Darja Wischerath, Daniel Racek, Douglas A. Parry, Emily Godwin, Joanne Hinds, Dirk Van Der Linden, Jonathan F. Roscoe, Laura Ayravainen, and Alicia G. Cork. 2023. "Platform-Controlled Social Media APIs Threaten Open Science." *Nature Human Behaviour* 7 (November): 2054–57. https://doi.org/10.1038/s41562-023-01750-2.

Dietz, Patricia M., Charles E. Rose, Dedria McArthur, and Matthew Maenner. 2020. "National and State Estimates of Adults with Autism Spectrum Disorder." *Journal of Autism and Developmental Disorders* 50 (12): 4258–66. https://doi.org/10.1007/s10803-020-04494-4.

Entertainment Software Association. 2025. "2025 Essential Facts about the u.s. Video Game Industry." Washington D.C.: Entertainment Software Association. https://www.theesa.com/resources/essential-facts-about-the-us-video-game-industry/2025-data/.

Es, Karin Van, and Dennis Nguyen. 2025. "Binge-Watching Netflix? Insights from Data Donations." *Media and Communication* 13 (February): 9362. https://doi.org/10.17645/mac.9362.

Flanagan, Mary, and Geoff Kaufman. 2017. "Shifting Implicit Biases with Games Using Psychology." In *Diversifying Barbie and Mortal Kombat: Intersectional Perspectives and Inclusive Designs in Gaming*, edited by Yasmin B. Kafai, Gabriela T Richard, and Brendesha M Tynes, 219–33. Pittsburgh: Carnegie Mellon University. https://doi.org/10.1184/R1/6686738.

Gardner, Daniel L., and Theresa Jean Tanenbaum. 2018. "Dynamic Demographics: Lessons from a Large-Scale Census of Performative Possibilities in Games." In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12. Montreal QC Canada: ACM. https://doi.org/10.1145/3173574.3173667.

Gerling, Kathrin Maria, Frank Paul Schulte, Jan Smeddinck, and Maic Masuch. 2012. "Game Design for Older Adults: Effects of Age-Related Changes on Structural Elements of Digital Games." In *Entertainment Computing - ICEC 2012*, edited by Marc Herrlich, Rainer Malaka, and Maic Masuch, 7522:235–42. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-33542-6_20.

González-González, Carina S., Pedro A. Toledo-Delgado, Vanesa Muñoz-Cruz, and Joan Arnedo-Moreno. 2022. "Gender and Age Differences in Preferences on Game Elements and Platforms." *Sensors* 22 (9): 3567. https://doi.org/10.3390/s22093567.

Gottfried, Jeffrey, and Olivia Sidoti. 2024. "Teens and Video Games Today." Pew Research Center. https://www.pewresearch.org/wp-content/uploads/sites/20/2024/05/PI_2024.05.09_Video-Games_REPORT.pdf.

Ha, Seungyeon, and Seongcheol Kim. 2024. "Barriers to Playing Digital Games: Why Do Some People Choose Not to Play Digital Games?" *Telematics and Informatics* 93 (September): 102161. https://doi.org/10.1016/j.tele.2024.102161.

Harnadi, Bernardinus, Albertus Dwiyoga Widiantoro, Fx Hendra Prasetya, Ridwan Sanjaya, and Ranto Partomuan Sihombing. 2025. "Role of Age, Gender and Cultural Factors as Moderator on Technology Acceptance of Online Entertainment." *Information Discovery and Delivery* 53 (1): 72–89. https://doi.org/10.1108/IDD-02-2023-0017.

Hughes, Nathan GJ, and Paul Cairns. 2020. "Player Trait Questionnaires: An (in)validation Study." Preprint. 10.31219/osf.io/kehmu.

Isorna Folgar, Manuel, José M. Faílde Garrido, María D. Dapía Conde, and Fátima Braña Rey. 2024. "Evaluation of Problematic Video Game Use in Adolescents with ADHD and Without ADHD: New Evidence and Recommendations." *Behavioral Sciences* 14 (7): 524. https://doi.org/10.3390/bs14070524.

Jones, Shawn Suyong Yi, Annie Harrisson, Sâmia Pedraça, Jessie Marchessault-Brown, Dmitri Williams, and Mia Consalvo. 2025. "The Virtual Census 2.0: A Continued Investigation on the Representations of Gender, Race, and Age in Videogames." *New Media & Society*, May, 14614448251336427. https://doi.org/10.1177/14614448251336427.

Kahn, Adam S., Rabindra Ratan, and Dmitri Williams. 2014. "Why We Distort in Self-Report: Predictors of Self-Report Errors in Video Game Play." *Journal of Computer-Mediated Communication* 19 (4): 1010–23. https://doi.org/10.1111/jcc4.12056.

Kaufman, Geoff, Mary Flanagan, and Gili Freedman. 2019. "Not Just for Girls: Encouraging Cross-Gender Role Play and Reducing Gender Stereotypes with a Strategy Game." In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 481–93. Barcelona Spain: ACM. https://doi.org/10.1145/3311350.3347177.

Kirk, Roger E. 1996. "Practical Significance: A Concept Whose Time Has Come." *Educational and Psychological Measurement* 56 (5): 746–59. https://doi.org/10.1177/0013164496056005002.

Kordyaka, Bastian, Luisa Pumplun, Marlies Brunnhofer, Bjoern Kruse, and Samuli Laato. 2023. "Gender Disparities in Esports – an Explanatory Mixed-Methods Approach." *Computers in Human Behavior* 149 (December): 107956. https://doi.org/10.1016/j.chb.2023.107956.

Larrieu, Maxime, Yoann Fombouchet, Joël Billieux, and Greg Decamps. 2023. "How Gaming Motives Affect the Reciprocal Relationships Between Video Game Use and Quality of Life: A Prospective Study Using Objective Playtime Indicators." *Computers in Human Behavior* 147 (October): 107824. https://doi.org/10.1016/j.chb.2023.107824.

Lee, Yu-Hao, and Mo Chen. 2023. "Seeking a Sense of Control or Escapism? The Role of Video Games in Coping with Unemployment." *Games and Culture* 18 (3): 339–61. https://doi.org/10.1177/15554120221097413.

Liu, Chuang-Chun. 2016. "Understanding Player Behavior in Online Games: The Role of Gender." *Technological Forecasting and Social Change* 111 (October): 265–74. https://doi.org/10.1016/j.techfore.2016.07.018.

Lopez-Fernandez, Olatz, A. Jess Williams, Mark D. Griffiths, and Daria J. Kuss. 2019. "Female Gaming, Gaming Addiction, and the Role of Women Within Gaming Culture: A Narrative Literature Review." *Frontiers in Psychiatry* 10 (July): 454. https://doi.org/10.3389/fpsyt.2019.00454.

Mazurek, Micah O., Christopher R. Engelhardt, and Kelsey E. Clark. 2015. "Video Games from the Perspective of Adults with Autism Spectrum Disorder." *Computers in Human Behavior* 51 (October): 122–30. https://doi.org/10.1016/j.chb.2015.04.062.

McClure, Robert F. 1985. "Age and Video Game Playing." *Perceptual and Motor Skills* 61 (1): 285–86. https://doi.org/10.2466/pms.1985.61.1.285.

McClure, Robert F., and F. Gary Mears. 1984. "Video Game Players: Personality Characteristics and Demographic Variables." *Psychological Reports* 55 (1): 271–76. https://doi.org/10.2466/pr0.1984.55.1.271.

Millington, Elliot, David R. Simmons, and Heather Cleland Woods. 2022. "Brief Report: Investigating the Motivations and Autistic Traits of Video Gamers." *Journal of Autism and Developmental Disorders* 52 (3): 1403–7. https://doi.org/10.1007/s10803-021-04994-x.

Norman, Justin. 2020. "In-App Ad Segmentation 101: How to Split and Analyse Your Players." *Gamesindustry.biz*, October. https://www.gamesindustry.biz/in-app-ad-segmentation-101.

Parry, Douglas A., Brittany I. Davidson, Craig J. R. Sewall, Jacob T. Fisher, Hannah Mieczkowski, and Daniel S. Quintana. 2021. "A Systematic Review and Meta-Analysis of Discrepancies Between Logged and Self-Reported Digital Media Use." *Nature Human Behaviour* 5 (May): 1535–47. https://doi.org/10.1038/s41562-021-01117-5.

Phan, Mikki H., Jo R. Jardina, Sloane Hoyle, and Barbara S. Chaparro. 2012. "Examining the Role of Gender in Video Game Usage, Preference, and Behavior." *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 56 (1): 1496–1500. https://doi.org/10.1177/1071181312561297.

Porter, John R., and Julie A. Kientz. 2013. "An Empirical Study of Issues and Barriers to Mainstream Video Game Accessibility." In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility*, 1–8. Bellevue Washington: ACM. https://doi.org/10.1145/2513383.2513444.

Ratan, Rabindra A., Nicholas Taylor, Jameson Hogan, Tracy Kennedy, and Dmitri Williams. 2015. "Stand by Your Man: An Examination of Gender Disparity in *League of Legends*." *Games and Culture* 10 (5): 438–62. https://doi.org/10.1177/1555412014567228.

Ream, Geoffrey L., Luther C. Elliott, and Eloise Dunlap. 2013. "Trends in Video Game Play Through Childhood, Adolescence, and Emerging Adulthood." *Psychiatry Journal* 2013: 1–7. https://doi.org/10.1155/2013/301460.

Santos, Ana Cláudia Guimarães, Wilk Oliveira, Julita Vassileva, Juho Hamari, and Seiji Isotani. 2025. "The Relationship Between Gamification User Types, Demographic Factors, and Gaming Habits." *International Journal of Human–Computer Interaction* 41 (18): 11806–20. https://doi.org/10.1080/10447318.2024.2446498.

Spiel, Katta, and Kathrin Gerling. 2021. "The Purpose of Play: How HCI Games Research Fails Neurodivergent Populations." *ACM Transactions on Computer-Human Interaction* 28 (2): 1–40. https://doi.org/10.1145/3432245.

Staley, Brooke S., Lara R. Robinson, Angelika H. Claussen, Samuel M. Katz, Melissa L. Danielson, April D. Summers, Sherry L. Farr, Stephen J. Blumberg, and Sarah C. Tinker. 2024. "Attention-Deficit/Hyperactivity Disorder Diagnosis, Treatment, and Telehealth Use in Adults — National Center for Health Statistics Rapid Surveys System, United States, October–November 2023." *MMWR. Morbidity and Mortality Weekly Report* 73 (40): 890–95. https://doi.org/10.15585/mmwr.mm7340a1.

Tondello, Gustavo F., and Lennart E. Nacke. 2019. "Player Characteristics and Video Game Preferences." In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '19*, 365–78. Barcelona, Spain: ACM Press. https://doi.org/10.1145/3311350.3347185.

Vornhagen, Jan B., April Tyack, and Elisa D. Mekler. 2020. "Statistical Significance Testing at CHI PLAY: Challenges and Opportunities for More Transparency." In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 4–18. Virtual Event Canada: ACM. https://doi.org/10.1145/3410404.3414229.

Vuorre, Matti, David Zendle, Elena Petrovskaya, Nick Ballou, and Andrew K. Przybylski. 2021. "A Large-Scale Study of Changes to the Quantity, Quality, and Distribution of Video Game Play During a Global Health Pandemic." *Technology, Mind, and Behavior* 2 (4): 1–8. https://doi.org/10.1037/tmb0000048.

Wang, Bingqing, Laramie Taylor, and Qiusi Sun. 2018. "Families That Play Together Stay Together: Investigating Family Bonding Through Video Games." *New Media & Society* 20 (11): 4074–94. https://doi.org/10.1177/1461444818767667.

Wilhelm, Claudia. 2018. "Gender Role Orientation and Gaming Behavior Revisited: Examining Mediated and Moderated Effects." *Information, Communication & Society* 21 (2): 224–40. https://doi.org/10.1080/1369118X.2016.1271902.

Williams, Dmitri, Mia Consalvo, Scott Caplan, and Nick Yee. 2009. "Looking for Gender: Gender Roles and Behaviors Among Online Gamers." *Journal of Communication* 59 (4): 700–725. https://doi.org/10.1111/j.1460-2466.2009.01453.x.

Williams, Dmitri, Nicole Martins, Mia Consalvo, and James D. Ivory. 2009. "The Virtual Census: Representations of Gender, Race and Age in Video Games." *New Media & Society* 11 (5): 815–34. https://doi.org/10.1177/1461444809105354.

Williams, Dmitri, Nick Yee, and Scott E. Caplan. 2008. "Who Plays, How Much, and Why? Debunking the Stereotypical Gamer Profile." *Journal of Computer-Mediated Communication* 13 (4): 993–1018. https://doi.org/10.1111/j.1083-6101.2008.00428.x.

Yap, Valerie, Amira Skeggs, Amanda M Ferguson, Amelia Leyland-Craggs, Laura Boeschoten, Kasper Welbers, Sebastian Kurten, and Amy Orben. 2024. "Digital Data Donation with Adolescents." PsyArXiv. https://doi.org/10.31234/osf.io/hnvpy.

Yee, Nick. 2006. "Motivations for Play in Online Games." *CyberPsychology & Behavior* 9 (6): 772–75. https://doi.org/10.1089/CPB.2006.9.772.

Yee, Nick, and Jeremy Bailenson. 2007. "The Proteus Effect: The Effect of Transformed Self-Representation on Behavior." *Human Communication Research* 33 (3): 271–90. https://doi.org/10.1111/j.1468-2958.2007.00299.x.

Yin, Junming, Yue (Katherine) Feng, and Yong Liu. 2025. "Modeling Behavioral Dynamics in Digital Content Consumption: An Attention-Based Neural Point Process Approach with Applications in Video Games." *Marketing Science* 44 (1): 220–39. https://doi.org/10.1287/mksc.2020.0180.

Zendle, David, Catherine Flick, Darel Halgarth, Nick Ballou, Simon Demediuk, and Anders Drachen. 2023. "Cross-Cultural Patterns in Mobile Playtime: An Analysis of 118 Billion Hours of Human Data." *Scientific Reports* 13 (1): 386. https://doi.org/10.1038/s41598-022-26730-w.

Zhang, Lin, Zhen Shao, Xiaotong Li, and Yuqiang Feng. 2021. "Gamification and Online Impulse Buying: The Moderating Effect of Gender and Age." *International Journal of Information Management* 61 (December): 102267. https://doi.org/10.1016/j.ijinfomgt.2020.102267.