Not All Play is Equal: In-game Player Behaviour Predicts Wellbeing Differences

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Large-scale studies using digital trace data consistently find that playtime alone is not meaningfully associated with wellbeing. Yet these studies typically capture playtime across platforms and titles without examining what happens inside a game: the granular in-game behaviours that might differentiate players' experiences. The Integrated Model of Player Experience posits that the mechanics and contexts players encounter during play shape the resulting experience and its downstream psychological effects, implying that players who engage with the same game in qualitatively different ways may report different wellbeing outcomes. We tested this using telemetry-driven profiling of session-level behavioural data from 412 players of the online shooter Plants vs. Zombies: Battle for Neighborville. Cluster analysis on 10 standardised performance and mode-preference metrics identified three distinct playstyles: exploratory, high-performing, and competitive. Exploratory players reported greater wellbeing and enjoyment than competitive players. However, we found no evidence that playstyle moderated the relationship between playtime and either outcome. These findings indicate that how players engage with a game's mechanics and modes is associated with different average levels of wellbeing, but we know little about how such playstyles might alter the relationship between the amount of play and wellbeing.

Keywords: video games, playstyle, wellbeing, play experience, telemetry

Introduction

The debate about whether video games harm or improve wellbeing has persisted for decades, yet empirical findings remain mixed and often shift with the methodological approaches used to study them. Earlier studies relying on players' retrospective estimates of their own playtime and behaviour produced contradictory findings. Several studies reported negative associations between self-reported playtime and measures of mental health or wellbeing (Ferguson & Colwell, 2019; Liu et al., 2019; Mathur & VanderWeele, 2019), with some reporting negative associations only among highly engaged players (Colder Carras et al., 2017; Przybylski & Weinstein, 2017). Other studies found positive associations (Halbrook et al., 2019; Villani et al., 2018), with some reporting these only for moderate usage (Przybylski & Weinstein, 2017) or specific game genres such as MMOs (Raith et al., 2021). To overcome the well-documented inaccuracy of self-reported measures (Johannes et al., 2021; Parry et al., 2021), later work utilised digital trace data (i.e., objective behavioural logs collected directly from game platforms). These studies demonstrated that associations between the average player's playtime and wellbeing are small and unlikely to be practically meaningful (Ballou, Földes, Vuorre, et al., 2025; Egami et al., 2024; Johannes et al., 2021; Larrieu et al., 2023; Vuorre et al., 2022).

These small, mixed, and often null results do not necessarily imply that playing video games is irrelevant to wellbeing. Rather, they suggest that the most measured dimension of play, its quantity, might not be the most important factor. In a large-scale analysis of adult Nintendo players, playtime was indeed not meaningfully related to multiple wellbeing indicators, but players' subjective evaluations of gaming's life-fit (e.g. the perceived harmful or beneficial value of gaming across various life domains outside of play) were (Ballou, Vuorre, et al., 2025). The underlying problem is that, conceptually, 'video game play' does not capture a single phenomenon, but instead hetero-

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geneous exposures such as 'playing with friends', 'succeeding or failing at the game's mechanics', or 'playing to alleviate study-related stress'. More generally, playtime can be thought to consist of context-centred exposures (e.g., when and with whom one plays), game-centred exposures (e.g., game modes, mechanics, and business models), and player-centred exposures (e.g., playstyles, motivations, and player experience) (Ballou, Hakman, et al., 2025). When studies collapse these layers into a single playtime variable, they conflate qualitatively distinct exposures and risk both theoretical ambiguity and empirical inconsistency (Ballou, Hakman, et al., 2025).

This highlights a crucial gap: while existing digital trace research is a mile wide in its scope of game platforms and genres, it is only an inch deep in actual player experiences and behaviours. Existing studies capture playtime across platforms and titles, but not what happens inside a game: the granular in-game behaviours and experiences that might explain why some players benefit from play while others do not. Quantity alone is insufficient; two players can accumulate the same playtime yet have markedly different player experiences. To reconcile the mixed historical findings with the contemporary null results, research needs to start modelling the quality of play using in-game digital trace data. Nevertheless, how researchers should best study in-game player experience empirically without reverting to subjective self-reports remains an open question.

One theoretically grounded operationalisation comes from the Integrated Model of Player Experience [IMP; Elson et al. (2014)], which identifies three categories of game characteristics that shape the playing experience: narrative (story and setting), mechanics (rules, interaction demands, and feedback), and context (the social and situational embedding). Where user-centric theories such as self-determination theory (Ryan et al., 2006) and uses and gratifications (Ruggiero, 2000) focus primarily on motivations and player states, the IMP is game-centric and focuses on how interaction with specific in-game characteristics during play alters the play experience and subsequent wellbeing outcomes (Elson et al., 2014). In this sense, the IMP opens the "black box" of in-game behaviour by connecting the game characteristics players encounter during play to the outcomes that follow, thereby guiding empirically testable hypotheses about these relationships (Elson et al., 2014). Crucially, the IMP positions mechanics as the foundational element of player experience; without mechanics there is no play, whereas narrative and context contribute situationally. A conceptually meaningful operationalisation of play quality should therefore incorporate digital trace data on mechanics-relevant indicators (e.g., performance metrics), contextual indicators (e.g., mode selection), and narrative indicators (e.g., dialogue engagement), where appropriate.

Within game analytics research, a similar categorisation process is known as telemetry-driven profiling, where collections of in-game behaviours, events, and experiences are condensed into behavioural profiles, or playstyles, that describe how players engaged with a game during the measurement period (Drachen et al., 2014; Ravari et al., 2022). Playstyles are distinct from player types. Player types refer to stable individual characteristics assessed via self-reports, as in Bartle's taxonomy (Bartle, 1996), which categorises players as Achievers, Explorers, Socializers, or Killers based on their preferences for achievement versus exploration and interaction with the game world versus other players; Yee's motivation model (Yee, 2006), which identifies three primary components of player motivation (i.e., achievement, social, and immersion); and the Hexad framework (Tondello et al., 2016), which proposes six gamification user types grounded in self-determination theory. The utility of such typologies has, however, been called into question by recent evidence of their temporal instability. Santos et al. (2023) found that 72% of participants changed their player type classification over six months, suggesting that self-reported types may not reliably reflect actual in-game behaviour.

In contrast, telemetry-derived playstyles capture emergent behavioural patterns as they occur, providing a more ecologically valid representation of how players engage with games. As such, playstyles offer a quantifiable, data-driven way to characterise how players pursue a game's objectives (Sifa et al., 2018). Previous work has used telemetry-driven profiling to examine the relationship between playstyles and personality (Bean & Groth-Marnat, 2016; van Lankveld et al., 2011), motivation (Melhart et al., 2019; Yee, 2016), national culture (Ravari et al., 2022), and individual and team performance (Jiang et al., 2021). However, whether and how playstyles relate to wellbeing and enjoyment has remained untested, in large part because datasets combining granular session-level behavioural telemetry with validated measures of wellbeing are exceedingly rare (Norwood et al., 2026).

The present study addresses three questions by leveraging one such dataset, collected through an industry-academia collaboration (Johannes et al., 2021). First, can distinct playstyles be identified from in-game behavioural telemetry within a single game title? Second, do players with different playstyles report different levels of wellbeing or enjoyment? Third, does the association between playtime and wellbeing or enjoyment differ between playstyles?

Methods

In this study, we analysed data reported in Johannes et al. (2021), who collected digital trace data and survey responses of 518 Plants versus Zombies: Battle for Neighborville players.

Plants versus Zombies: Battle for Neighborville

Plants versus Zombies: Battle for Neighborville (PvZ) is an online third-person multiplayer shooter released by Electronic Arts (EA) in October 2019. Players can choose from 23 customisable gameplay classes, each with unique weapons, abilities, and movement styles. The game offers a range of competitive Player-versus-Player (PvP) modes, including objective-based matches, team deathmatches, and 2v2 arena matches. It also features several Player-versus-Environment (PvE) open zones with storylines, quests, collectables, and side missions. Players can earn experience points and in-game currencies, using the former to indicate progression and the latter to upgrade and buy new characters. The game was available on PC, PS4, Xbox One, and Nintendo Switch (Electronic Arts, 2019).

Participants

As detailed in Johannes et al. (2021), participants were recruited by Electronic Arts directly from its active player base via email invitations sent in two waves: the first in early August 2020 to 50,000 players, and the second in late September 2020 to 200,000 players. In total, 518 PvZ players completed the wellbeing survey (an approximate 0.21% response rate). For details on the full dataset, which also includes Animal Crossing: New Horizons players, see Johannes et al. (2021). Because our research questions concern mechanics-based playstyles, we applied several inclusion criteria to ensure the analytic sample consisted of players who actively engaged with the game's core mechanics. We first excluded participants without matching telemetry data (n = 48). We then excluded 57 participants without telemetry across any activity (PvP or PvE). These players spent time in the game's social hub, an idle space for navigation and character customisation, but did not participate in any gameplay and thus had no behavioural data from which to derive playstyle profiles. The final analytic sample consisted of 412 combat-active players (M age = 35, SD = 11.8; 318 male, 81 female, 1 other, 12 undisclosed), representing 79.5% of the original 518 respondents. Following the original paper's methodology, values more than 6 standard deviations from a variable's mean were replaced with NA on a case-by-case basis (Johannes et al., 2021). In this dataset, this procedure replaced 87 values (across 48 variables; 26 participants affected) and did not reduce the final analytic sample.

Measures

Playtime

The first measure we calculated was playtime, though determining it is already complex. Simply measuring the total time an account has been online does not distinguish between active and idle time. Idle time refers to periods when a player's account is online but they are not actively engaging with the objectives or mechanics of the game. This can occur when a player is away from the keyboard, but it can also include time spent in home screens, customisation menus, lobbies, and social spaces. In this study, active playtime was calculated by aggregating session data. Sessions represent the different levels, game modes, or worlds a player can inhabit. Every player is always in a session and can only be in one session at a time; however, multiple players can be in the same session. For example, when a player launches PvZ, they enter the hub world, where they can choose which level or mode to play. Entering the hub world starts the session timer, which ends when they choose a level or leave to join a match; this, in turn, starts a new session timer for that level. In total, the 412 players in our sample played 36,621 sessions, of which 25,937 occurred in the two weeks prior to survey completion. These sessions took place across 19 different maps facilitating different forms of gameplay: 13,594 Player-versus-Player (PvP) sessions (51.27%), 4,854 Player-versus-Environment (PvE) sessions (18.31%), and 7,489 Social Hub sessions (28.24%). After excluding the social hub sessions, this left 17,505 total sessions: 12,445 PvP sessions (71.09%) and 4,509 PvE sessions (25.76%). Visual inspection suggested that players had distinctive preferences for which game modes they chose to play and when (Figure 1).

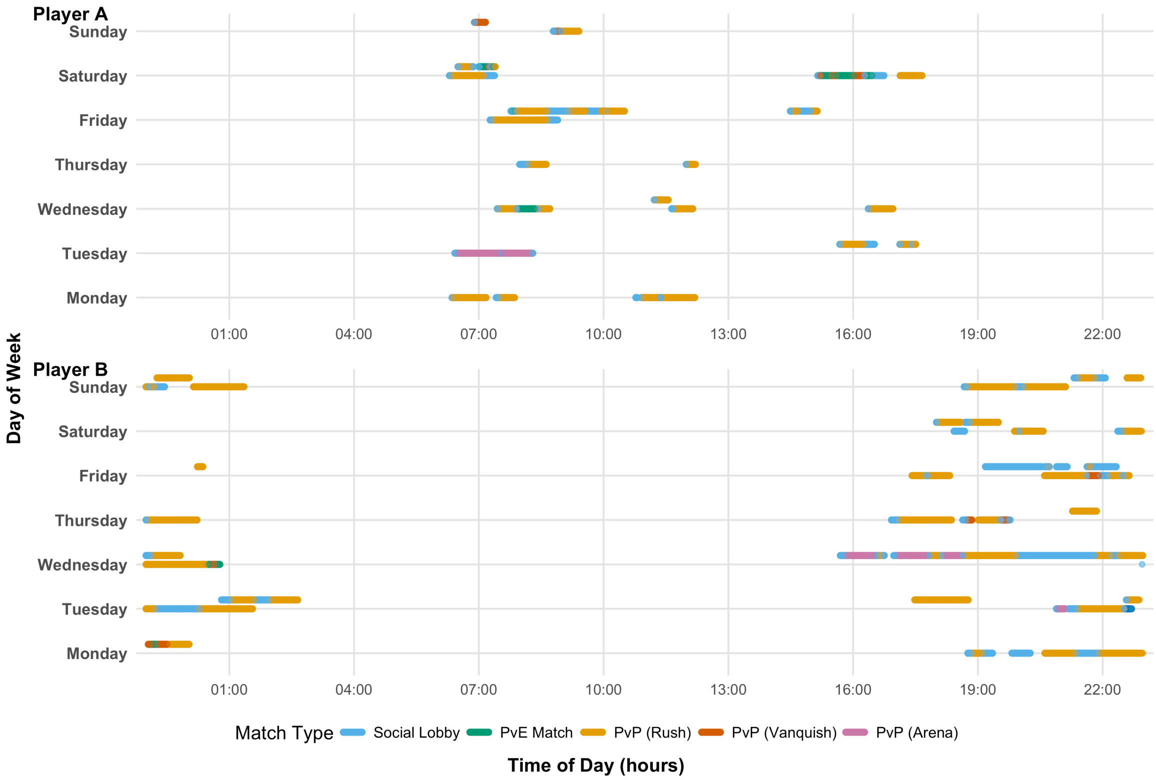

Figure 1. Session timelines for two example players showing gaming activity across the two-week study period. Each horizontal bar represents a gaming session, with colours indicating match type (Social Lobby, PvE Match, PvP Rush/Vanquish/Arena). Each player's panel contains two rows corresponding to the two weeks of telemetry data, collapsed onto a single weekly timeline to facilitate comparison of play patterns across weeks.

Behavioural telemetry

The raw telemetry contained session-based records of in-game events for each player. From these records, we selected and computed metrics only if they had been previously validated as informative measures of player behaviour and performance in shooter games (Drachen et al., 2012; Lugrin et al., 2013; Melhart et al., 2019). Two principles guided the computation of the behavioural metrics. First, all performance metrics were constructed to be independent of total playtime. Common cumulative indicators such as 'player level' or 'total kills' were deliberately excluded because they conflate skill with playtime; a player's level may simply be higher because they played more, not because they performed better. Second, every metric was computed separately for PvP and PvE modes, because the two contexts differ fundamentally in difficulty, objectives, and opponent type; eliminating a computer-controlled enemy in PvE is not comparable to eliminating a matchmade opponent of similar rank in PvP. Pooling across modes would obscure meaningful behavioural differences. This resulted in 12 behavioural metrics plus one overall playtime measure (for descriptive statistics, see Table 1). Mode ratio captured the proportion of active playtime each player devoted to PvP and PvE modes, reflecting game-mode preference. Kill/death ratio indexed combat effectiveness as the number of eliminations per death, with higher values indicating greater survivability and lethality. Hit accuracy measured the proportion of shots that connect with a target, reflecting aiming precision. Damage per second captured sustained offensive output, indicating how efficiently a player dealt damage over time. Average damage per game reflected total offensive contribution within a match, encompassing both direct combat and area-of-effect output. Average score per game provided a composite performance indicator incorporating objectives completed, assists, and other in-game scoring events beyond raw combat. Each of these five performance metrics was computed separately for PvP and PvE, yielding 10 mode-specific indicators alongside the two mode-ratio variables.

Table 1. Descriptive Statistics for Key Variables

Variable	M	SD	Min	Max
Age	35.01	11.77	18	99
Total Hours Played	9.47	11.7	0.15	69.33
Proportion of PvP Playtime	0.47	0.28	0	1
Proportion of PvE Playtime	0.25	0.24	0	1
PvP Kill/Death Ratio	12.76	38.16	0	387.62
PvE Kill/Death Ratio	55.18	88.75	0	725
PvP Hit Accuracy	0.27	0.12	0	0.83
PvE Hit Accuracy	0.4	0.13	0	0.87
PvP Damage per Second	4.86	4.05	0	24.9
PvE Damage per Second	11.8	12.61	0	124.62
PvP Average Damage per Game	2731.45	2502.23	0	15093
PvE Average Damage per Game	8231.29	6501.59	0	34232.25
PvP Average Score	1654.94	1033.57	0	5505
PvE Average Score	2620.9	2404.79	0	20725
Wellbeing (SPANE)	2.95	1.91	−4	6
Enjoyment	5.82	1.11	1.75	7

N = 412. Gender distribution: Female: 81 [19.7], Male: 318 [77.2], Other: 1 [0.2], Prefer not to say: 12 [2.9]

Wellbeing

We assessed affective wellbeing with the Scale of Positive and Negative Experiences [SPANE; Diener et al. (2010); Diener et al. (2018)]. Respondents were prompted to reflect on how they felt over the past two weeks and rated how often they experienced each of six positive (positive, good, pleasant, happy, joyful, contented) and six negative (negative, bad, unpleasant, sad, afraid, angry) feelings on a scale from 1 (Very rarely or never) to 7 (Very often or always). An overall wellbeing balance score was computed by subtracting the mean negative score from the mean positive score, yielding a possible range of −6 to +6, where higher values indicate more positive affect.

Enjoyment

Enjoyment was assessed with four items from the Player Experience and Need Satisfaction scale [PENS; Ryan et al. (2006)], validated by Johnson et al. (2018). The full PENS comprises subscales measuring autonomy, competence, relatedness, enjoyment, and extrinsic motivation; we used only the four-item enjoyment subscale, which captures hedonic appreciation of the play experience. Respondents were asked to reflect on their experience playing PvZ over the past two weeks and rated items such as “I think PvZ was fun to play” on a scale from 1 (Strongly disagree) to 7 (Strongly agree).

Data analysis

Data were analysed in R version 4.5.1 (R Core Team, 2025). Key packages included `fpc` for cluster validation indices (Hennig, 2020), `factoextra` for multivariate visualisation (Kassambara & Mundt, 2020), and `robustlmm` for robust mixed-effects estimation (Koller, 2016).

Following initial data cleaning, all survey responses were screened for straightlining (e.g. when respondents give identical answers to all items) to identify records with low data quality commonly found in online surveys (Leiner, 2019); however, no unusual cases were identified. Afterwards, the telemetry records were matched to the same two-week window referenced by the survey items, and analyses were conducted on active players with sufficient mode-specific telemetry.

To test whether clustering was appropriate before fitting any cluster model, we evaluated cluster tendency using three complementary approaches. First, we computed the Hopkins statistic (Banerjee & Dave, 2004), which compares distances in observed data to distances expected under spatial randomness; values near 0.5 indicate random structure, whereas larger values indicate clusterable structure. Second, we used Visual Assessment of Cluster Tendency (VAT) (Bezdek & Hathaway, 2002), which reorders the dissimilarity matrix so potential clusters appear as darker diagonal blocks. Third, we examined Principal Component Analysis (PCA) projections to assess whether separable groupings were visible in low-dimensional space relative to random reference data. Together, these diagnostics indicated non-random structure suitable for clustering.

We then identified playstyles with Partitioning Around Medoids (PAM) (Kaufman & Rousseeuw, 1990) on standardised in-game behavioural features. PAM was selected over k-means because it is less sensitive to extreme points and defines each cluster by an observed medoid (a real player profile), which improves robustness and interpretability for telemetry-derived behavioural profiles. Features were z-standardised before clustering, and missing mode-specific performance values were set to zero to encode no activity in that mode rather than dropping cases. The number of clusters was determined by maximising the Calinski-Harabasz index across k = 2 to 10 (Tibshirani et al., 2001), which selected a three-cluster solution; we then checked internal coherence with silhouette widths (Kaufman & Rousseeuw, 1990).

To examine associations between playstyle, playtime, and outcomes, we fit robust linear mixed-effects models (Koller, 2016). Robust estimation was preferred over standard maximum-likelihood mixed models because telemetry-derived playtime and performance metrics are characteristically right-skewed and prone to influential observations; a small number of highly engaged players can exert disproportionate leverage on ordinary least-squares estimates. Robust estimation downweights such influential cases automatically through iteratively reweighted least squares, yielding coefficient estimates that better reflect the bulk of the sample without requiring ad hoc outlier exclusion rules that introduce researcher degrees of freedom. This approach also maintains methodological consistency with our clustering strategy: PAM was selected precisely because it is less sensitive to extreme points, and using a robust estimator at the modelling stage carries that same design philosophy through the analytic pipeline. All models included random intercepts for country to account for baseline between-country differences; random slopes were not estimated because the number of countries was too small to support the additional parameters reliably. Outcomes were treated as continuous and approximately normally distributed, and playtime was entered on its raw scale. Approximate p-values were derived from the normal reference distribution for t-statistics, and 95% confidence intervals were computed as $b \pm 1.96 \times \mathrm{SE}$. We used simple-slopes analyses to estimate within-playstyle playtime slopes and pairwise slope-difference tests to compare those slopes across playstyles. Statistical significance was set at $p < .05$.

Data, Materials, and Code

The present study was not preregistered. The data and code reported in this study can be found at https://osf.io/fngzc. The raw data, materials, codebook, and further details on the dataset shared by Johannes et al. (2021) can be found at https://osf.io/cjd6z/.

Results

RQ1. Player Clustering Analysis

Assessing Cluster Tendency

The Hopkins statistic computed from our player behavioural data was high (0.8844, 95% CI [0.8443, 0.9245]), substantially exceeding the 0.70 threshold and indicating strong cluster tendency. As a validity check, a random dataset with identical dimensions produced a substantially lower value (0.63), closer to the 0.5 benchmark expected under spatial randomness. VAT plots showed clear dark diagonal blocks for the player data, consistent with separable groups, while the random reference data showed no comparable block structure (Appendix 1; Bezdek & Hathaway (2002)). PCA visualisations converged on the same conclusion, with visible grouping in the player data but not in the random comparison. The convergence of these three independent assessments (Hopkins, VAT, and PCA) provided strong statistical evidence to reject the null hypothesis of spatial randomness, demonstrating that the player behavioural data contained meaningful, non-random structure amenable to clustering methods.

PAM Clustering

To select the number of clusters, we evaluated PAM solutions for k = 2 to 10 using the Calinski-Harabasz (CH) index, where higher values indicate better separation relative to within-cluster dispersion (Kaufman & Rousseeuw, 1990; Tibshirani et al., 2001). The CH index peaked at k = 3 (Appendix 2), supporting a three-cluster solution as the best trade-off between fit and parsimony.

Having selected k = 3 on the basis of the CH index, we assessed the internal validity of this solution using silhouette analysis (Kaufman & Rousseeuw, 1990), which quantifies how well each observation fits its assigned cluster relative to the nearest neighbouring cluster. The average silhouette width was 0.22. According to Kaufman and Rousseeuw's interpretive guidelines, values above 0.25 indicate strong structure and values between 0.10 and 0.25 indicate weak but still meaningful structure; the overall value thus falls at the boundary, suggesting reasonable separation. Per-cluster silhouette widths ranged from 0.15 to 0.39, with one cluster exceeding the 0.25 threshold and the remaining two showing acceptable cohesion. No negative silhouette values were observed, confirming that every observation was assigned to its most appropriate cluster. The substantive interpretation of these three clusters is presented below.

Interpretation of Clusters

Following established approaches to telemetry-based player profiling (Bauckhage et al., 2015; Drachen et al., 2012; Drachen et al., 2014; Melhart et al., 2019; Sifa et al., 2018), we labelled the three clusters on the basis of their dominant mode preferences and performance levels (Figure 2). The labels reflect two dimensions that emerged from the data: the game mode players predominantly engaged with (PvE vs. PvP) and their overall performance level (casual vs. elite).

Casual PvP Players (22.1% of the sample) devoted the majority of their time to competitive PvP modes (70.7%), yet their performance was moderate (PvP K/D: M = 7.79; PvP Accuracy: M = 21.8%), falling well below Elite Allround Players. Performance in PvE was similarly modest. This pattern indicates a preference for competitive engagement that is not accompanied by correspondingly high skill, suggesting a casual orientation to play within a competitive context.

Casual PvE Players (19.9% of the sample) allocated the majority of their playtime to cooperative PvE modes (58.6%), achieving moderate performance within that context (PvE K/D: M = 63.59; PvE Accuracy: M = 40.2%) while showing markedly lower metrics in PvP. This profile suggests a specialisation in story-driven exploration and cooperative play over competitive engagement.

Elite Allround Players (58% of the sample), the largest cluster, maintained high performance across both gameplay contexts, with kill-to-death ratios and accuracy rates substantially above the sample mean in both PvP (K/D: M = 17.19; Accuracy: M = 31.5%) and PvE (K/D: M = 71.91; Accuracy: M = 42%). Rather than specialising in one mode, these players engaged broadly and performed well regardless of context, distinguishing them as the most proficient segment.

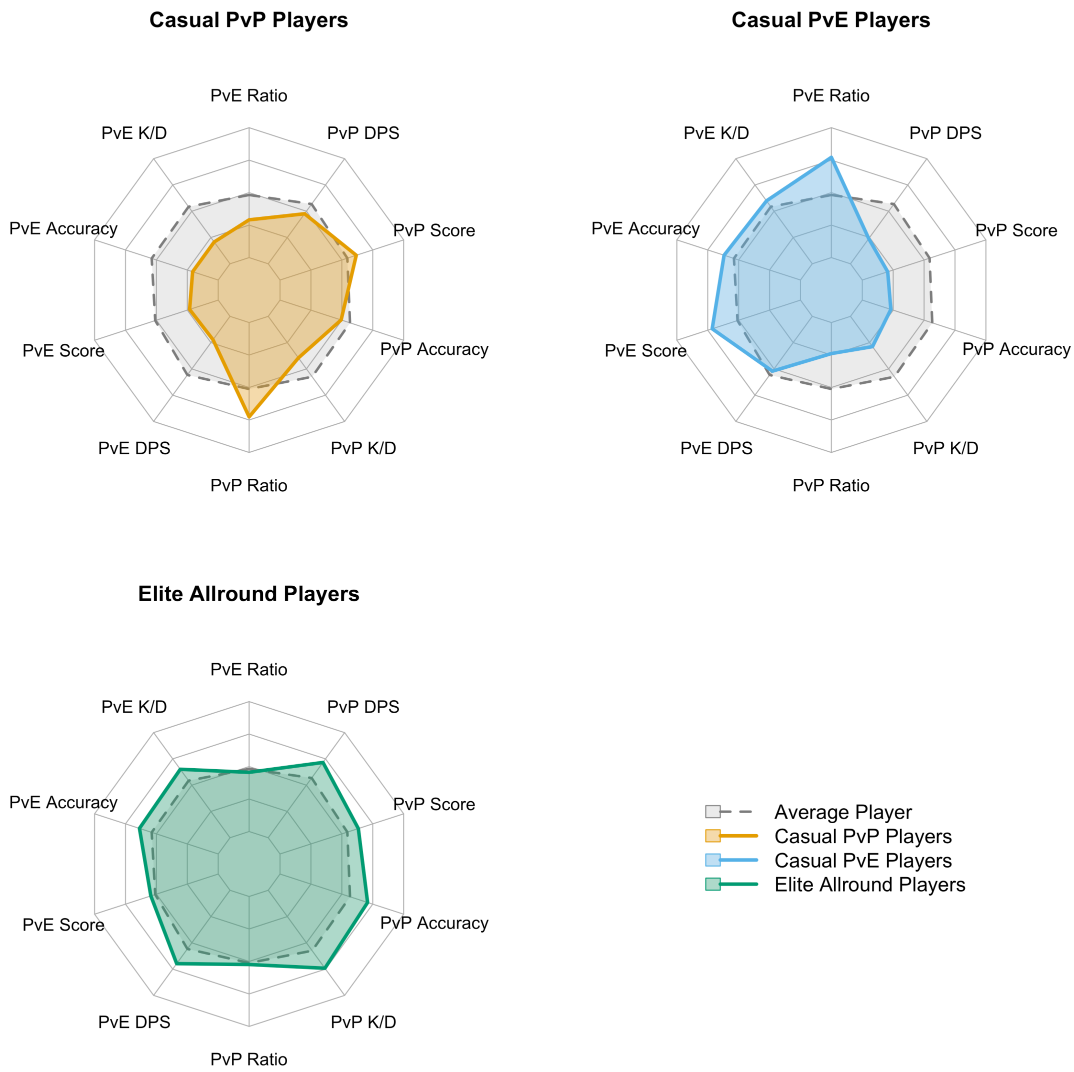

Figure 2. Radar charts showing performance and mode selection for each playstyle relative to the playstyle of the average player (dashed line). Values are standardized mean scores (z-scores converted to 0-1 scale). Mean values: Casual PvE Players (PvP Ratio: 0.17, PvE Ratio: 0.59, PvP K/D: 4.88, PvE K/D: 63.59); Elite Allround Players (PvP Ratio: 0.49, PvE Ratio: 0.22, PvP K/D: 17.19, PvE K/D: 71.91); Casual PvP Players (PvP Ratio: 0.71, PvE Ratio: 0.03, PvP K/D: 7.79, PvE K/D: 1.24). PvE = Player versus Environment; PvP = Player versus Player; K/D = Kill/Death ratio; DPS = Damage per second.

RQ2. Wellbeing differences between player types

For each outcome (wellbeing and enjoyment), we estimated a main-effects model predicting the outcome from player type, hours played, gender, and age, with random intercepts for country (outcome ~ player_type + hours + gender + age + (1 | country); see Appendix 3). The fixed effects accounted for a modest share of outcome variance (wellbeing: marginal $R^2 = 0.093$, conditional $R^2 = 0.093$; enjoyment: marginal $R^2 = 0.061$, conditional $R^2 = 0.061$). Casual PvE Players served as the reference category. Relative to these players, both Casual PvP Players ($b = -0.91$, 95% CI [−1.48, −0.33], $t = -3.11$, $p = 0.002$) and Elite Allround Players ($b = -0.89$, 95% CI [−1.38, −0.40], $t = -3.55$, $p < .001$) reported significantly lower wellbeing. For enjoyment, Casual PvP Players again scored lower than Casual PvE Players ($b = -0.47$, 95% CI [−0.78, −0.15], $t = -2.93$, $p = 0.003$), whereas the difference between Elite Allround and Casual PvE Players was smaller and not statistically reliable (b = −0.28, 95% CI [−0.55, −0.01], t = −2.05, p = 0.040) (see Figure 3).

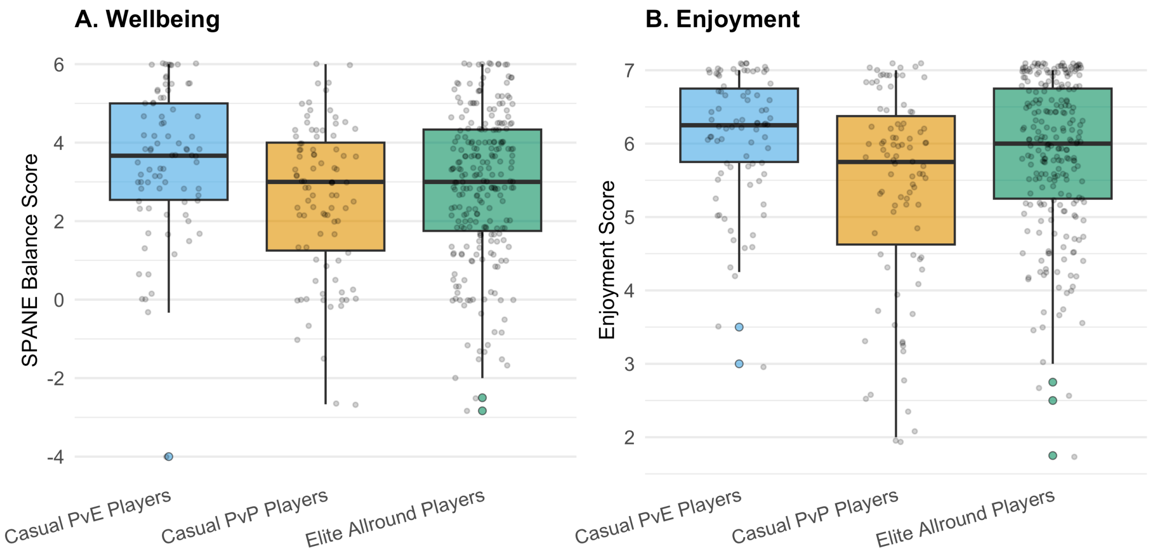

Figure 3. Distribution of wellbeing outcomes by play style. Panel A shows wellbeing (SPANE balance score); Panel B shows enjoyment. Boxes represent interquartile ranges with median lines; whiskers extend to 1.5 × IQR. Individual points show outliers.

RQ3. Does Playstyle Moderate the Playtime–Wellbeing Relationship?

To test whether the playtime–wellbeing association differed across playstyles, we extended the main-effects models by adding player type × hours interaction terms, retaining gender and age as covariates (outcome ~ player_type × hours + gender + age + (1 | country); see Appendix 4). Adding the interaction terms did not meaningfully increase variance explained (wellbeing: marginal R^2 = 0.093; enjoyment: marginal R^2 = 0.063). In the main-effects models, hours played was positively associated with both outcomes (wellbeing: b = 0.03, 95% CI [0.01, 0.04], t = 3.08, p = 0.002; enjoyment: b = 0.01, 95% CI [0.01, 0.02], t = 3.10, p = 0.002). Each interaction coefficient represents the difference in the playtime slope for a given playstyle relative to Casual PvE Players. None of the interaction terms reached significance: for wellbeing, neither Casual PvP Players (*<U+0394>b* = −0.02, 95% CI [−0.08, 0.05], t = −0.52, p = 0.600) nor Elite Allround Players (*<U+0394>b* = −0.00, 95% CI [−0.04, 0.04], t = −0.00, p = 0.998) had a playtime slope that differed from the reference group. The same held for enjoyment (Casual PvP: *<U+0394>b* = 0.01, 95% CI [−0.02, 0.05], t = 0.69, p = 0.493; Elite Allround: *<U+0394>b* = 0.00, 95% CI [−0.02, 0.03], t = 0.19, p = 0.851). Playstyle differences in intercepts remained in the interaction models, particularly for Casual PvP Players (wellbeing: b = −0.82, 95% CI [−1.48, −0.16], t = −2.44, p = 0.015; enjoyment: b = −0.54, 95% CI [−0.90, −0.17], t = −2.91, p = 0.004).

These playstyle differences were corroborated by one-way ANOVAs (wellbeing: F(2, 409) = 5.96, p = 0.003, η^2 = 0.028; enjoyment: F(2, 409) = 9.48, p < .001, η^2 = 0.044) and Tukey HSD post-hoc tests, which confirmed that Casual PvP Players scored lower than Casual PvE Players on both wellbeing (p = 0.002) and enjoyment (p < .001), and lower than Elite Allround Players on enjoyment (p = 0.001).

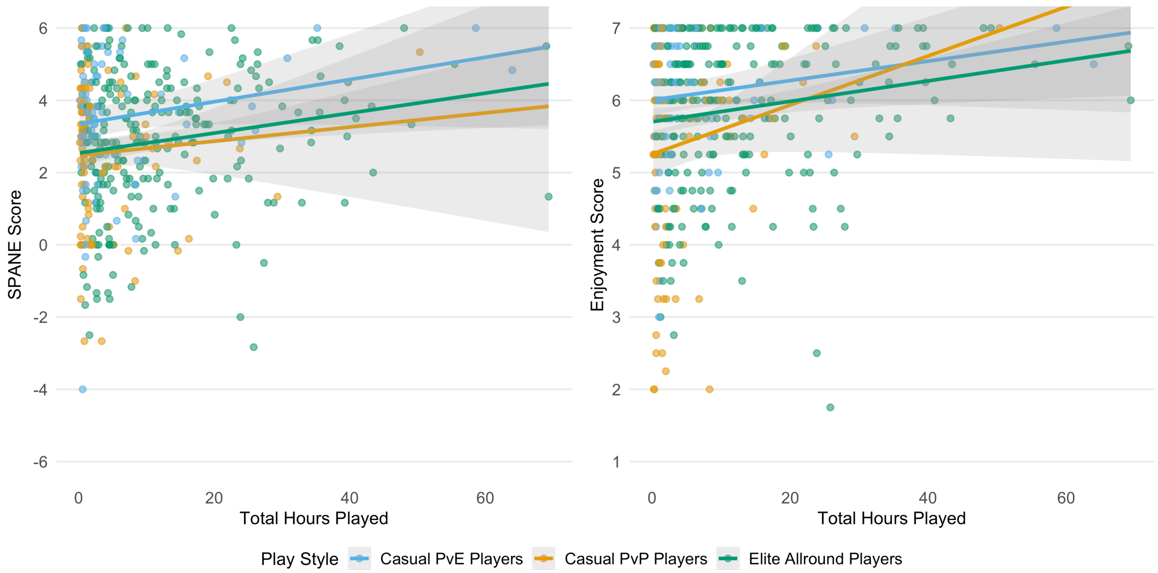

Figure 4. Interaction plots showing the relationship between hours played and psychological outcomes across playstyles. The left panel shows wellbeing (SPANE balance score), and the right panel shows enjoyment. Lines represent linear regression slopes with 95% confidence intervals. Casual PvE Players and Elite Allround Players show positive associations between playtime and outcomes, while Casual PvP Players show no significant relationship.

To further probe the interaction, simple slopes analyses decomposed the playtime–outcome association within each playstyle (Figure 4). Only Elite Allround Players showed a significant positive slope for both wellbeing (b = 0.028, p = 0.006) and enjoyment (b = 0.014, p = 0.013). Slopes for Casual PvE Players (wellbeing: b = 0.028, p = 0.137; enjoyment: b = 0.012, p = 0.258) and Casual PvP Players (wellbeing: b = 0.011, p = 0.682; enjoyment: b = 0.024, p = 0.102) were not significant. Critically, pairwise comparisons of slopes did not provide evidence that the playtime–outcome association differed between any pair of playstyles (all ps > .05), though the present sample may lack the power to detect small slope differences. Taken together, these results indicate that playstyle is associated with different average levels of wellbeing and enjoyment, but the data do not support the conclusion that the playtime–outcome relationship itself varies meaningfully across playstyles.

Discussion

The objectives of this study were twofold. First, we aimed to complement the breadth of platform-level playtime research with the depth of granular in-game playstyle analysis. Through telemetry-driven profiling, we aimed to demonstrate how players' in-game behavioural heterogeneity can be modelled within a single game. Second, informed by the Integrated Model of Player Experience, we sought to explore how players' interactions with game mechanics and preferences for different in-game modes shape their play experience and subsequent wellbeing, thereby providing greater insight into the conditions under which, and the players for whom, video game play might support or undermine wellbeing.

Accordingly, this study addressed three research questions: whether distinct playstyles can be identified from in-game behavioural telemetry within a single game; whether players with different playstyles report different levels of wellbeing and enjoyment; and whether the association between playtime and wellbeing outcomes differs across playstyles. In short, the findings support the first two questions but not the third. Three distinct playstyles were identified from behavioural telemetry and labelled to reflect two dimensions that emerged from the data: (1) preferred game mode (PvE vs. PvP) and (2) overall performance level (casual vs. elite). These playstyles were associated with meaningful differences in wellbeing and enjoyment, but we found no evidence that they moderated the relationship between playtime and wellbeing or enjoyment. The implications and limitations of these findings are discussed below.

The participants in the first cluster, named "Casual PvE Players", allocated the majority of their playtime to cooperative PvE modes, achieving moderate performance within that context while showing markedly lower metrics in PvP. This playstyle suggests a preference for story-driven exploration and cooperative play over competitive engagement, paralleling the "Adventurer" type identified by Melhart et al. (2019) in *Tom Clancy's The Division*, who similarly focused on solo and cooperative mission content rather than competitive play. We hypothesise that these players adopt a more recreation-oriented approach to play, gravitating toward narrative content and cooperative challenges that offer immediate enjoyment without the sustained pressure of competitive evaluation. This interpretation is consistent with the view that playstyle captures not only goal-directed behaviour but also forms of engagement partly motivated by the enjoyment that a particular way of playing produces (Kalmanlehto, 2025). Within the IMP framework (Elson et al., 2014), this pattern reflects a preference for game contexts in which narrative and exploratory mechanics are foregrounded over adversarial mechanics, potentially affording greater perceived autonomy over how to engage with the game's content and a lower threshold for competence satisfaction. Consistent with this interpretation, Casual PvE Players reported the highest wellbeing and enjoyment of the three groups. This finding is consistent with Melhart et al. (2019)'s observation that cooperative and exploratory play features were among the strongest predictors of need satisfaction in *The Division.*

The players in the second cluster, called "Elite Allround Players", formed the largest cluster. They maintained high performance across all gameplay contexts, with kill-to-death ratios and accuracy rates substantially above the sample mean in both PvP and PvE. Rather than specialising in one mode, these players engaged broadly and performed well regardless of context, distinguishing them as the most proficient segment. This playstyle is conceptually consistent with the "Elite" type in Melhart et al. (2019)'s analysis of *The Division*, characterised by top-tier progression metrics, and with the high-performing player segments identified by Drachen et al. (2012) in *Battlefield 2: Bad Company 2.* The breadth of their engagement suggests that mode preference alone does not define this group; rather, it is the consistent pursuit of high performance that characterises their play, consistent with a mastery- or achievement-oriented orientation in which players seek to develop and exercise skill across the full range of available game content. Despite their superior performance, however, Elite Allround Players reported lower wellbeing and enjoyment than Casual PvE Players, though higher enjoyment than Casual PvP Players. This pattern is noteworthy because prior work suggests that competence satisfaction positively predicts wellbeing in gaming contexts (Klimmt et al., 2009; Przybylski et al., 2010; Ryan & Deci, 2001; Tamborini et al., 2011). However, if competence alone drove wellbeing, the most skilled players should report the highest wellbeing. Our findings do not support this, suggesting that the context in which competence is exercised matters as well, consistent with the IMP's emphasis on both mechanics and context as jointly shaping player experience (Elson et al., 2014). Potentially, Elite Allround Players' broad engagement across both cooperative and competitive modes may dilute the wellbeing benefits that cooperative PvE environments appear to afford. Furthermore, their high skill may buffer against the competence frustration that competitive environments can impose on less proficient players, though without direct measurement, this remains speculative.

Finally, the players in the third cluster, called "Casual PvP Players", devoted the majority of their time to competitive PvP modes, yet their performance was moderate, falling well below that of Elite Allround Players. Their performance in PvE was similarly modest. This pattern indicates a preference for competitive engagement that is not accompanied by correspondingly high skill, suggesting a casual orientation to play within a competitive context. A comparable playstyle appears in Drachen et al. (2012)'s analysis of *Battlefield 2: Bad Company 2*, where a segment of players engaged frequently in competitive modes without achieving high performance metrics, and it bears some resemblance to the "Social Dark Zone Player" in Melhart et al. (2019)'s *Division* typology, who preferred competitive areas but were distinguished more by their social engagement than their skill. These players were potentially drawn to the multiplayer and competitive dynamics of PvP modes rather than to the mastery of competitive mechanics per se. This combination of competitive exposure and moderate skill may create a less optimal play experience. Competitive PvP environments are characterised by direct performance feedback, social comparison, and outcome uncertainty, conditions that could frustrate competence needs when players lack the skill to succeed consistently (Ballou, Hakman, et al., 2025). Consistent with this reasoning, Casual PvP Players reported the lowest wellbeing and enjoyment of the three groups. The finding that competitive engagement at moderate skill levels is associated with the poorest psychological outcomes aligns with evidence that need frustration in gaming contexts can undermine wellbeing (Ballou, Hakman, et al., 2025) and suggests that the experiential costs of competitive play may not be offset by the social or excitement-related benefits that draw these players to PvP modes.

Lastly, we found no evidence that playstyle moderates the association between playtime and wellbeing or enjoyment. Although Elite Allround Players showed the only significant positive simple slope, this did not translate into a significant difference from the slopes of other groups. These findings align closely with Johannes et al. (2021), who tested whether self-reported player experiences moderated the playtime-wellbeing association in the same game, *Plants vs. Zombies: Battle for Neighborville*. They found that neither need satisfaction, nor enjoyment, nor extrinsic motivation significantly interacted with playtime in predicting wellbeing, concluding that player experience contributes to wellbeing independently rather than altering how playtime relates to it. Our study extends this result by testing moderation through an entirely different operationalisation, objectively measured behavioural playstyles derived from telemetry, rather than self-reported motivational experiences. That neither subjective player experience nor objective behavioural profile moderates the playtime-wellbeing association in this game strengthens the case that playtime alone is not meaningfully associated with wellbeing for most players (Ballou, Földes, Vuorre, et al., 2025; Johannes et al., 2021; Vuorre et al., 2022).

It is worth noting, however, that the absence of moderation in our data does not constitute evidence that playtime is wholly irrelevant to wellbeing under all conditions. The playtime-wellbeing relationship is subject to a wide range of time-varying confounds, including physical health, grief, work stress, and leisure availability, that can bias observed associations in either direction (Ballou, Földes, Hakman, et al., 2025). Our cross-sectional design and limited set of covariates leave open the possibility that such confounds obscure true differential effects. Moreover, our study examines only one game; it remains possible that playstyle-by-playtime interactions exist in games with greater mechanical diversity, stronger competitive ranking systems, or more pronounced social features. The null moderation finding should therefore be interpreted as specific to the present context rather than as a general claim about the impossibility of such effects.

What the data do show is that the playtime paradigm is incomplete in a critical respect; it misses qualitative differences in play that are associated with meaningful variation in average wellbeing. Playtime treats all minutes of play as equivalent, but players who devote their time to cooperative PvE gameplay report higher wellbeing than those who spend comparable time in competitive PvP modes. This between-group difference in levels, rather than in slopes, is the primary empirical contribution of the present study. In this respect, our results complement rather than contradict platform-level research; playtime may indeed be uninformative as a predictor of wellbeing, but the behavioural composition of that playtime is not.

Limitations & Future Work

Several limitations constrain the interpretation of these findings and point toward productive directions for future research. First, the study examines a single game with a specific player population recruited by the developer, and we lack evidence that the identified playstyles generalise to other games, genres, or player populations. Unlike personality traits, playstyles may be contextual and fluid, shaped by the interaction between a game's design elements and the player's ludic habitus, that is, their accumulated gameplay experiences and skills (Jaćević, 2022). As such, a player's playstyle in one game may not predict their behaviour in another with different mechanics or competitive structures. This also means that playstyles should not be assumed to reflect stable personality characteristics (Kalmanlehto, 2025); the profiles identified here describe how players engaged with this particular game during the study period, not enduring individual differences.

Second, while our behavioural telemetry provided comprehensive metrics on core gameplay mechanics and performance, it captured only a subset of potential in-game behaviours. Notably absent were indicators of social interaction, which is an important dimension of multiplayer gaming experiences that the IMP identifies as part of the contextual layer of player experience (Elson et al., 2014). In this study, sessions spent in the game's social hub were considered idle time and thus excluded from the playstyle analysis because these sessions generated no mechanics-relevant telemetry on which to cluster. Yet recent work has shown that ostensibly idle or non-interactive periods in games, including socialising between matches and exploring social spaces, can serve experiential functions such as community-building and strategic preparation that shape the broader play experience (Tepponen et al., 2025). Future work could address this gap by extending the playstyle profiling framework to incorporate social and communicative dimensions of gameplay. Gesture-based digital trace data, such as the 'ping' communication systems common in multiplayer games, have been demonstrated to be related to game context, team dynamics, and performance outcomes (Zheng & Farzan, 2023).

Third, the cross-sectional design precludes causal inference. The observed associations between playstyle and wellbeing may reflect selection effects (e.g., players with higher baseline wellbeing may gravitate toward cooperative play) rather than the influence of play behaviour on outcomes. This concern is not merely hypothetical; a wide range of time-varying confounds, from physical health conditions to work stress, plausibly affect both what players do in games and how they feel (Ballou, Földes, Hakman, et al., 2025). Our design cannot disentangle whether cooperative PvE play promotes wellbeing, whether wellbeing promotes cooperative play, or whether both are driven by unmeasured third variables.

Conclusion

This study demonstrates that players of the same game engage with it in qualitatively different ways and that these differences are associated with meaningful variation in wellbeing and enjoyment. However, we found no evidence that playstyle moderates the playtime-wellbeing relationship. These findings contribute to the growing body of digital trace research in two respects. First, they provide empirical support for the view that gameplay constitutes heterogeneous exposures with distinct psychological correlates, even within a single title. Second, they demonstrate a practical methodology, telemetry-driven profiling, for incorporating in-game behavioural depth into wellbeing research. At the same time, the null moderation results caution against overclaiming: the present data show that what players do is associated with how they feel, but not that different styles of play change how playtime itself relates to wellbeing. As richer forms of in-game data become available through industry-academia partnerships, researchers should continue to develop more granular, theory-driven approaches to understanding player experience and its relationship to psychological outcomes.

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Author contributions

Conceptualization: TH, AKP; Data curation: TH, MV; Formal analysis: TH, MV; Funding acquisition: AKP; Investigation: TH; Methodology: TH, MV; Project administration: AKP; Supervision: MV, AKP; Visualization: TH; Writing – original draft: TH; Writing – review & editing: TH, MV, AKP

Conflicts of Interest

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(2022–2024), the Google Expert Advisory on Youth and Technology (2025), the OpenAI Expert Council on Wellbeing and AI (2025), and UK Department for Science, Innovation and Technology–funded research on children's smartphone and social media use (University of Cambridge, 2025). He is a member of the UK Department for Culture, Media & Sport College of Experts. Any industry fees are directly donated to charity, and his research is conducted in accordance with University of Oxford academic integrity policies.

Ethics

The study procedures were granted ethical approval by the University of Oxford's Central University Research Ethics Committee (OII_C1A_23_107). The original data collection was approved under SSH_OII_CIA_21_011 (Johannes et al., 2021). All participants provided informed consent and reported being 18 years or older.

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A1 Appendix

A1.1 Appendix 1: Cluster Tendency Assessment

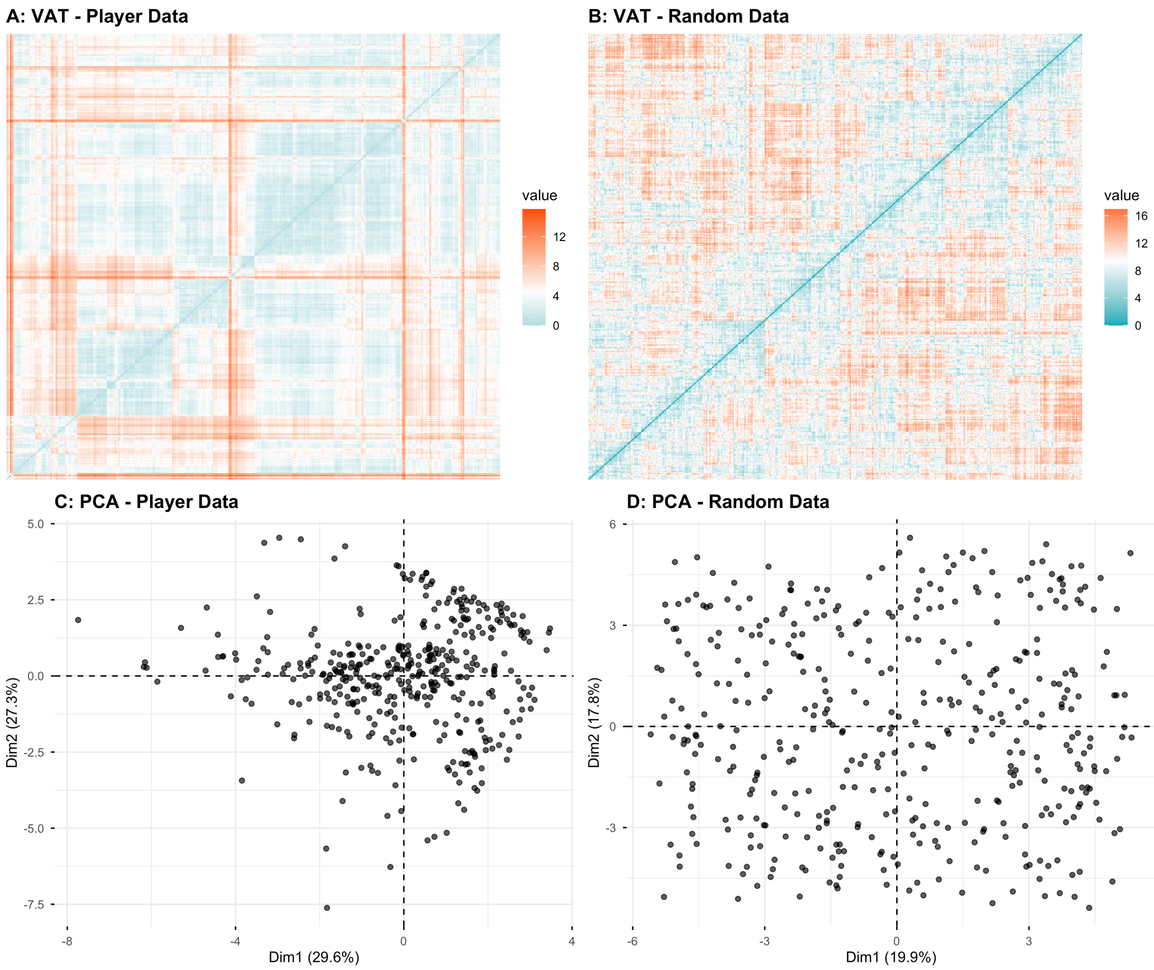

Figure A1.1. Cluster tendency assessment comparing player data (left column) to random data (right column). Top row: Visual Assessment of Cluster Tendency (VAT) ordered dissimilarity matrices. Bottom row: PCA visualizations. The player data shows clear clustering structure (dark blocks in VAT, visible groupings in PCA) while random data shows no such patterns.

A1.2 Appendix 2: Cluster Validation Plots

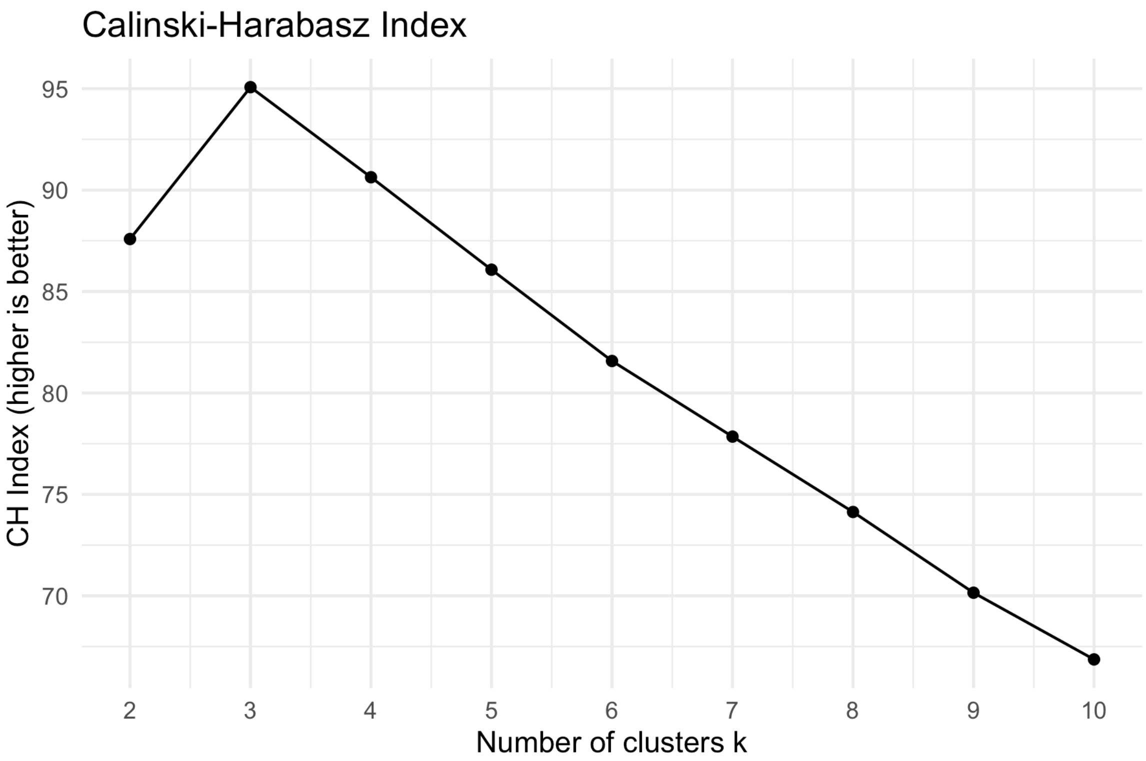

Figure A1.2. Cluster validation using the Calinski-Harabasz Index across k = 2 to 10.

The plot above shows the validation method used to determine the optimal number of clusters. The Calinski-Harabasz Index evaluates cluster validity based on the ratio of between-cluster to within-cluster variance, with higher values indicating better separation between clusters. The index indicated that k = 3 was the optimal number of clusters for our player data.

A1.3 Appendix 3: Robust Mixed-Model Coefficients

Model	Outcome	Term	b	SE	t	p
Main effects	Wellbeing	Casual PvP vs Casual PvE	−0.906	0.292	−3.11	0.002
Main effects	Wellbeing	Elite Allround vs Casual PvE	−0.887	0.25	−3.55	< .001
Main effects	Wellbeing	Hours played	0.026	0.008	3.08	0.002
Main effects	Wellbeing	Gender: Male (vs Female)	−0.788	0.239	−3.3	< .001
Main effects	Wellbeing	Gender: Other (vs Female)	−4.424	1.926	−2.3	0.022
Main effects	Wellbeing	Gender: Undisclosed (vs Female)	−0.844	0.593	−1.42	0.154
Main effects	Wellbeing	Age	−0.016	0.008	−2	0.046
Main effects	Enjoyment	Casual PvP vs Casual PvE	−0.468	0.16	−2.93	0.003
Main effects	Enjoyment	Elite Allround vs Casual PvE	−0.281	0.137	−2.05	0.040
Main effects	Enjoyment	Hours played	0.014	0.005	3.1	0.002
Main effects	Enjoyment	Gender: Male (vs Female)	−0.213	0.131	−1.63	0.103
Main effects	Enjoyment	Gender: Other (vs Female)	−0.79	1.054	−0.75	0.453
Main effects	Enjoyment	Gender: Undisclosed (vs Female)	−0.436	0.324	−1.35	0.178
Main effects	Enjoyment	Age	−0.003	0.004	−0.71	0.481
Moderation	Wellbeing	Casual PvP vs Casual PvE	−0.822	0.338	−2.44	0.015

Model	Outcome	Term	b	SE	t	p
Moderation	Wellbeing	Elite Allround vs Casual PvE	−0.899	0.3	−2.99	0.003
Moderation	Wellbeing	Hours played	0.028	0.019	1.49	0.136
Moderation	Wellbeing	Gender: Male (vs Female)	−0.803	0.24	−3.34	< .001
Moderation	Wellbeing	Gender: Other (vs Female)	−4.421	1.932	−2.29	0.022
Moderation	Wellbeing	Gender: Undisclosed (vs Female)	−0.865	0.595	−1.45	0.146
Moderation	Wellbeing	Age	−0.016	0.008	−1.97	0.048
Moderation	Wellbeing	Casual PvP x Hours	−0.017	0.033	−0.52	0.600
Moderation	Wellbeing	Elite Allround x Hours	0	0.021	0	0.998
Moderation	Enjoyment	Casual PvP vs Casual PvE	−0.537	0.185	−2.91	0.004
Moderation	Enjoyment	Elite Allround vs Casual PvE	−0.292	0.164	−1.77	0.076
Moderation	Enjoyment	Hours played	0.012	0.01	1.13	0.257
Moderation	Enjoyment	Gender: Male (vs Female)	−0.203	0.132	−1.54	0.123
Moderation	Enjoyment	Gender: Other (vs Female)	−0.799	1.058	−0.76	0.450
Moderation	Enjoyment	Gender: Undisclosed (vs Female)	−0.413	0.326	−1.27	0.205
Moderation	Enjoyment	Age	−0.003	0.004	−0.71	0.475
Moderation	Enjoyment	Casual PvP x Hours	0.012	0.018	0.69	0.493
Moderation	Enjoyment	Elite Allround x Hours	0.002	0.012	0.19	0.851

This table presents the full coefficient estimates for all four robust mixed-effects models. ANOVA omnibus tests, Tukey HSD post-hoc comparisons, simple slopes, and pairwise slope-difference tests are reported in the main text.