

All BANG, little buck: Need-related experiences are weakly linked with behavior in the video game domain

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Psychological theories of media use often assume that subjective motivation affects observable behavior. Using video games as a test case, we examine this assumption by pairing repeated self-reports of motivation with objective digital trace data at scale. Across two datasets comprising tens of thousands of hours of gaming behavior, we test predictions derived from self-determination theory and the Basic Needs in Games (BANG) model, which posit that autonomy, competence, and relatedness experiences drive engagement. Study 1 (preregistered) analyzes 11k daily observations from 555 U.S. players with 30 days of multi-platform digital trace data. Study 2 (exploratory) examines 102k sessions from 9k PowerWash Simulator players, linking in-game experience prompts to behavioral logs. In both studies, need satisfaction was robustly associated with subjective states but showed weak or null associations with short-term gaming behavior, including subsequent play, session length, and return latency, across extensive preregistered and robustness analyses. These findings reveal a substantial motivation–behavior gap and suggest that SDT-based accounts may overestimate the role of need satisfaction in explaining when or how much people play. Data and code are available under a CC0 license at <https://doi.org/10.5281/zenodo.18352505>.

Keywords: motivation, digital trace data, video games, self-determination theory, displacement, compensatory behavior
Words: 9629

Introduction

Digital technology use constitutes one of the domains in which behavior is most directly observable. Digital media (1) are widely used—upwards of half of adults and nearly all children in the UK and US regularly play video games (Entertainment Software Association, 2024; Ofcom, 2023); (2) generate digital trace data (automatically logged histories of user behavior), and (3) affect the health of at least some users in important ways, both for better and for worse (Ballou, Hakman, et al., 2024; Granic et al., 2014). These putative impacts of media use behavior on health are of interest to users, industry professionals, policymakers, clinicians, and families, but research to date has had limited success supporting these groups (Ballou, 2023). Among other difficulties, progress has been stymied by three challenges: (1) accessing granular behavioral data, (2) measuring mental health with sufficient temporal detail, and (3) aligning theory with growing evidence that effects relate primarily to the quality, rather than quantity, of play (Ballou & Deterding, 2024; Büchi, 2024; Orben, 2022).

Digital trace data—histories of user actions generated when interacting with games—addresses several of these challenges. Compared to self-report, trace data provides greater detail about what, when and how much people play while alleviating concerns about recall biases (Ernala et

al., 2020; Kahn et al., 2014; Parry et al., 2021). However, three key limitations remain. First, while gaming companies collect player data at scale (El-Nasr et al., 2021), these data are rarely accessible to independent researchers. Where access has been negotiated or engineered via open source methods, it typically covers just one game or platform. While single-game studies can offer high depth and detail, they are potentially a small part of a person’s gaming diet—engaged UK and US players use an average of 2.8 platforms (Ballou, Vuorre, et al., 2025). Given this, we advocate for openly available digital trace data spanning both single-game studies and multi-platform data access to understand holistic effects.

Second, while trace data is often richly longitudinal, it has to date only been paired with wellbeing surveys consisting of either a single measurement wave (Ballou, Vuorre, et al., 2025; Johannes et al., 2021) or waves separated by multiple weeks (Larrieu et al., 2023; Vuorre et al., 2022). Early evidence suggests gaming effects may materialize and dissipate within 6 hours (Ballou, Vuorre, et al., 2025; Vuorre, Ballou, et al., 2023), and subjective wellbeing varies substantially across a day (Luhmann et al., 2021). Experience sampling and daily diary methods, embraced in social media research (Aalbers et al., 2021; Siebers et al., 2021), are needed to capture nuanced, short-lived effects and to better differentiate within- and between-person relationships (Johannes et al., 2024).

Third, effects of gaming are likely nuanced and contextual, but existing research lacks strong theoretical frameworks to guide investigation. Studies using digital trace data have ruled out simple playtime–wellbeing rela-

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tionships (Ballou, Sewall, et al., 2024; Ballou, Vuorre, et al., 2025; Johannes et al., 2021; Larrieu et al., 2023; Vuorre et al., 2022), supporting calls to move beyond quantity-focused approaches (Ballou, Hakman, et al., 2025). To do so, we need theory-driven predictions about how psychological states relate to gaming behavior itself—what motivates people to play in the first place, and how daily fluctuations in wellbeing shape engagement patterns. Self-Determination Theory (SDT, Ryan, 2023a) offers such a framework, proposing that satisfaction of basic psychological needs—autonomy, competence, and relatedness—drives motivated behavior including media use. Understanding whether and when people choose to play games may depend critically on their experiences of needs satisfaction in daily life, yet the majority of studies that have tested these behavioral predictions did so without access to intensive longitudinal data (Allen & Anderson, 2018; e.g., Bender & Gentile, 2019).

Together, these gaps point to clear next steps: collect digital trace data in the form of both comprehensive multi-platform records and single-game, granular interactions; pair it with high-resolution, repeated wellbeing measurements; and use this data for theory-driven investigations of play quality and context. These are the aims of the present study.

Self-determination theory

Self-determination theory (Ryan & Deci, 2017) proposes three innate and universal psychological needs: the need for autonomy (to feel in control over one's life and volitional in one's actions), competence (to act effectively and exert mastery in the world), and relatedness (to feel that one is valued by others and values them in return). These basic psychological needs are theorized to be direct antecedents of intrinsic and autonomous motivation, as well as vital nutrients required for a person to live a fully functional life (Ryan, 2023b). Across the environments we inhabit and activities we perform, these needs can be either satisfied or frustrated (Vansteenkiste et al., 2020).

There has been substantial research into how games and other entertainment media can support basic psychological needs (Przybylski et al., 2010; Tyack & Mekler, 2020). Games are adept at satisfying all three basic needs; games that better satisfy needs are more engaging; and having one's needs satisfied during gaming is associated with better mental health outcomes during and after play (Reer & Quandt, 2020; Tyack & Mekler, 2020; Vella & Johnson, 2012). A large body of work supports that basic need satisfaction supports intrinsic motivation, and intrinsic motivation translates to higher self-reported behavioral engagement (Ryan et al., 2022).

The Basic Needs in Games (BANG) Model

The Basic Needs in Games (BANG) model of video game play and mental health (Ballou & Deterding, 2024) builds upon the core SDT principle that any action's impact on mental health is mediated by the extent to which it satisfies or frustrates basic psychological needs. By differentiating between playtime and quality of play, BANG seeks to ex-

plain seemingly conflicting earlier findings that playtime itself is largely unrelated to wellbeing, but that some players do experience meaningful benefits or harms from their video game play.

To date, however, BANG remains largely untested. Hence, the goal of this study is to test several key BANG hypotheses. We label the hypotheses of the current study in numerical order (e.g., H1) but also provide the numbered label from the original paper (e.g., B6) for clarity of potential falsification.

The Relationship Between Basic Needs in Games and Global Basic Needs (H1)

Following the hierarchical model of intrinsic and extrinsic motivation (Vallerand, 1997), BANG conceives of basic needs as operating at three levels of generality: situational (a particular gaming session), contextual (gaming as a whole), and global (one's life in general). Experiences at lower levels of generality feed into and co-constitute higher levels—experiences with games are one (greater or lesser) element of one's life overall.

A positive relationship between need satisfaction in games and overall need satisfaction is well-established in prior literature (Allen & Anderson, 2018; Ballou, Denisova, et al., 2024; Bradt et al., 2024). BANG (B6) formalizes this relationship, proposing that need satisfaction experienced during gaming sessions contributes to overall need satisfaction in life. Thus, BANG hypothesizes:

H1. When individuals' in-game needs are better satisfied, they report greater overall need satisfaction.

Expectations (H2a)

Early articulations of SDT propose that goal or activity selection is (intrinsically) motivated by the 'awareness of potential satisfaction' of basic psychological needs or 'expectations about the satisfaction of those [salient] motives' (Deci & Ryan, 1985, pp. 231–239). Need-related outcome expectations are closely related to intrinsic motivation (perhaps even forming part of the computational machinery underlying motivation Murayama & Jach, 2023), and the behavioral product of these expectations is therefore greater behavioral engagement.

Expectations have, perhaps surprisingly, not featured prominently in subsequent empirical work; most gaming and media use-related SDT work focuses on need satisfaction or frustration as the experiential consequence of media consumption (Ballou & Deterding, 2023b). Need experiences can explain loops of self-sustaining activity, but cannot explain initial selective exposure to gaming where the activity has not commenced.

BANG proposes that experiences of need satisfaction during a particular gaming session positively affect players' expectations for future need satisfaction with the current game, similar games, and gaming as a whole. This prediction is grounded in reports that expected need frustration is reported to modulate both initial and continued gaming exposure (Ballou & Deterding, 2023a), and in broader findings that outcome expectations are a strong predictor of continued media engagement (Chang et al., 2014; Kocak Alan et al., 2022; Larose et al., 2001). From BANG (B8), we therefore derive the following hypothesis:

Table 1. Platform Details

Platform	Data Source	Account Linking Process	Type of Data Collected
Nintendo	Data-sharing agreements with Nintendo of America	Participants shared an identifier contained within a QR code on the Nintendo web interface. Nintendo of America uses this identifier to retrieve gameplay data and share it with the research team. ^a	Session records (what game was played, at what time, for how long) for first-party games only (games published in whole or in part by Nintendo). ^b
Xbox	Data-sharing agreement with Microsoft	Participants consented to data sharing by opting in to the study on Xbox Insiders with their Xbox account. Microsoft retrieved and shared pseudonymized gameplay data for all consented accounts. ^c	Session records (what game was played, at what time, for how long). Game titles were replaced with a random persistent identifier, but genre(s) and age ratings are shared.
Steam	Custom web app (Gameplay.Science)	Using a web app we developed (https://gameplay.science), participants consented to have their gameplay data monitored for the duration of the study. Authentication uses the official Steam API (OpenID).	Hourly aggregates per game (every hour, the total time spent playing each game during the previous hour)

^a See <https://accounts.nintendo.com/qrcode>.

^b Nintendo-published games accounted for 63% of Switch playtime in our sample.

^c See <https://support.xbox.com/en-US/help/account-profile/manage-account/guide-to-insider-program>.

H2a. When individuals' in-game need satisfaction is higher, they are more likely to play video games in the 24-hour period after survey completion.

Compensation (H2b)

SDT predicts that (global) need frustration results in compensatory behavior—people attempt to replenish needs that are not being met by altering their behavior (e.g., Sheldon et al., 2011). The potent need satisfaction offered by games constitute one way for people to compensate, particularly those who are highly engaged with gaming and have high gaming literacy (Ballou et al., 2022). The so-called “need density hypothesis” predicts that problematic or disordered gaming is most likely to occur when a person experiences high need satisfaction in games and high need frustration in other life domains (Rigby & Ryan, 2011). In other words, problematic gaming is theorized to occur, at least for some, due to a negative feedback loop whereby compensation occurs and becomes maladaptive such that the person's other compensatory tools besides gaming are progressively diminished. Several studies have found support for the need density hypothesis account (Allen & Anderson, 2018; Bradt et al., 2024; Mills et al., 2018).

BANG operationalizes this compensatory play via intrinsic motivation. Frustrated needs in one's life in general make opportunities to fulfill those needs more salient, which—all else equal—manifests phenomenologically as a stronger preference towards activities that satisfy the frustrated need(s). Given this, we hypothesize in the context of our sample of moderately to highly-engaged video game players (derived from BANG Hypothesis 9):

H2b. When individuals' global need frustration is higher, they are more likely to play video games in the 24-hour period after survey completion.

Displacement (H3)

Playtime, BANG argues, only becomes problematic when it displaces other activities essential to the maintenance of need satisfaction in life overall. Commonly proposed problematic displacements are work/school responsibili-

ties (Drummond & Sauer, 2020), personal relationships (Domahidi et al., 2018), and physical health or sleep (King et al., 2013). Displacing these essential activities would thereby reduce global need satisfaction. Thus, BANG (B5) hypothesizes:

H3. When a person's most recent gaming is reported to displace a core life domain (work/school, social engagements, sleep/eating/fitness, or caretaking), their global need satisfaction is lower.

Study 1: Preregistered Analysis of Multi-Platform Digital Trace Data and Daily Surveys

Study 1 was pre-registered on the Open Science Framework (OSF) in the form of a Stage 1 Programmatic Registered Report (Ballou, Földes, Hakman, et al., 2025). The present report is the first of three preregistered Stage 2 outputs; two other components, focused on sleep and genres, respectively, are forthcoming.

All data and analysis code are available on Zenodo (<https://doi.org/10.5281/zenodo.18352505>).

Study 1 Method

Design

The data for this study comprise a subset of the data from the Open Play study (Ballou, Földes, Vuorre, et al., 2025), version 1.0.0. In the Open Play study, participants provided access to automated records of their gaming history on one or more platforms (Xbox, Steam, Nintendo Switch, iOS, Android) and completed an intake survey followed by a 30-day daily diary study. The intake survey included demographic questions and baseline measures of wellbeing. Daily data was collected between Oct 2024 and Aug 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, self-reported playing video games for at least 1 hour per week, of which 50% must take place

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. iOS and Android data were collected but are not used in this analysis. For full details of the recruitment procedures and study methodology, see (Ballou, Földes, Vuorre, et al., 2025).

Ethics

This study received ethical approval from the Social Sciences and Humanities Inter-Divisional Research Ethics Committee at the University of Oxford (OII_CIA_23_107). 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.

Sample Size Justification

As specified in the Stage 1 Registered Report, sample size was determined by feasibility/resources rather than a formal power analysis, with an initial target of recruiting up to 1,000 U.S. participants into the diary component, with ~30% expected attrition. Sensitivity analyses showed that this sample size was sufficient to estimate target associations with moderate precision (95% CI spanning .13 scale points on a 7-point scale) (<https://github.com/digital-wellbeing/platform-study-rr>).

Participant Inclusion/Exclusion Criteria

All eligibility and exclusion criteria were specified prior to data analysis in Stage 1 and/or documented as deviations in Table 3. Participants were eligible if they were aged 18+, resided in the U.S., reported playing video games at least 1 hour/week, reported that a substantial share of their gaming occurred on eligible platforms (Nintendo/Xbox/Steam), and successfully linked at least one eligible account with validated recent digital trace data. As documented, two eligibility thresholds were adjusted for feasibility relative to Stage 1: the platform-share requirement was lowered (75% → 50%), and the recent valid trace requirement was extended (7 days → 14 days).

Participants who completed fewer than 15 daily surveys were excluded from the primary (imputed) analyses. The ≥15-survey threshold aligns with the Stage 1 criterion of avoiding analyses that would require imputing more data than collected (≥50%).

Participants

Table 2. Participant characteristics by sample

Characteristic	Full sample	Analytic sample
N	1208	555
Age (years)	25.4 (4.2)	28.0 (5.2)
Gender		
Man	393 (60.2%)	353 (63.6%)
Woman	225 (34.5%)	159 (28.6%)
Other gender identity	35 (5.4%)	43 (7.7%)
Ethnicity		
White	375 (61.5%)	354 (63.8%)
Black/African American	72 (11.8%)	49 (8.8%)
Asian	41 (6.7%)	56 (10.1%)
Multiracial	93 (15.2%)	71 (12.8%)
Other	29 (4.8%)	25 (4.5%)
Education		
Less than high school	15 (2.3%)	10 (1.8%)
High school or some college	360 (55.1%)	242 (43.6%)
Associate degree	71 (10.9%)	57 (10.3%)
Bachelor's degree	160 (24.5%)	206 (37.1%)
Graduate degree	37 (5.7%)	39 (7.0%)
Gaming behavior		
Weekly play (hours)	19.1 (12.5)	17.7 (11.4)
Study engagement		
Surveys completed	2.8 (3.6)	26.3 (3.9)

Values are M (SD) or N (%). Ethnicity and education categories collapsed to main levels for clarity.

The current sample included 555 participants (63.6% men, 28.6% women, 7.7% other gender identities) who completed at least 15 daily surveys and were included in the main imputed analyses. The full eligible sample comprised 1208 participants who completed at least 1 survey and were included in complete case sensitivity analyses.

Measures

The measures used in this paper are visualized in Figure 1 and detailed below. For other measures in the Open Play study not used here, we refer readers to the Open Play codebook (Ballou, Földes, Vuorre, et al., 2025).

Need satisfaction in games. We measured need satisfaction and frustration in games during the most recent gaming session using 3 items from an abbreviated version of the Basic Psychological Need Satisfaction in Gaming Scale (BANGS, Ballou & Deterding, 2024). The BANGS assesses autonomy, competence, and relatedness need satisfaction with three items for each need; we selected the highest-loading item for each need for our brief daily measure (e.g., relatedness satisfaction: “I felt I formed relationships with other players and/or characters.”). Participants rated each item on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). We calculated mean scores for need satisfaction by averaging all three items. Reliability of the composite 3-item need satisfaction index was

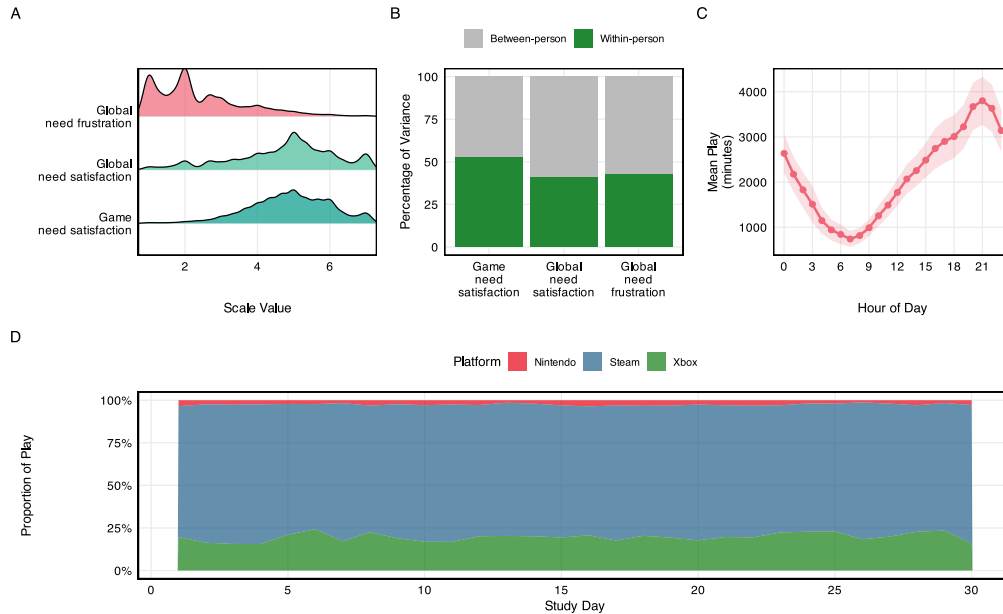


Figure 1. Descriptive statistics for key variables. (A) Distributions of need satisfaction and frustration variables. (B) Variance decomposition showing proportion of variance at within-person vs between-person levels. (C) Play volume by hour of day (local time). (D) Proportion of play on each platform across study days 1-30.

assessed using McDonald’s omega total ($\omega_t = 0.64$ for need satisfaction, $\omega_t = 0.65$ for need frustration). As needs are conceptually distinct, we expect lower reliability for the composite index than for unidimensional scales.

Need satisfaction and frustration in daily life. We measured need satisfaction and frustration in daily life (“global need satisfaction and frustration”) during the previous 24 hours using the brief version of the Basic Psychological Need Satisfaction and Frustration Scale (Chen et al., 2015; Martela & Ryan, 2024). This scale includes 6 items, with one item for need satisfaction and one item for need frustration for each of the three needs (e.g., “Today ... I was able to do things that I really want and value in life”). Participants rated each item on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). We calculated mean scores for need satisfaction and need frustration by averaging the relevant items. Reliability of the composite 3-item need satisfaction index was assessed using McDonald’s omega total ($\omega_t = 0.85$ for need satisfaction; $\omega_t = 0.73$ for need frustration). As needs are conceptually distinct, we expect lower reliability for this composite index than for unidimensional scales.

Video game playtime. We measured video game playtime using digital trace data collected from participants’ gaming accounts on Xbox, Steam, and Nintendo Switch. During the 30-day study period, we recorded a total of 862 hours of play on Nintendo Switch, 5,744 hours on Xbox, and 22,694 hours on Steam. For each daily survey, we calculated total minutes played in the 24-hour period following survey completion. We also created a binary variable indicating whether any play occurred during this period. On average, 51.6% of surveys were followed by any play in the subsequent 24 hours, with a mean of 111 minutes (SD = 171).

Displacement: We measured displacement of core life domains via an open text field asking participants about the hypothetical alternative activity: “Think back to your most recent gaming session. If you hadn’t played a game, what would you most likely have done instead?” With LLM assistance from Qwen3-4b-instruct (Qwen Team, 2025), we coded participant responses based on whether they mentioned any of the following activities: work/school responsibilities, social engagements, sleep/eating/fitness, or caretaking—so-called “core life domains”. We refined the LLM prompt through 5 iterations of manual verification of the 100 random coded responses. We created a boolean variable indicating whether any core life domain was hypothetically displaced. Full materials are provided in the supplement, including the exact LLM prompt used for classification, all raw participant responses, coded outputs, manual verification results, and reproducible code.

Data Exclusions

Consistent with Stage 1, we applied preregistered exclusions to telemetry records prior to analysis: we excluded telemetry days with >16 hours total logged play across linked platforms, sessions >8 hours, and sessions logged in the future (indicating logging error or system-clock manipulation). We also excluded survey responses failing the preregistered attention check (duplicate need item responses differing by >1 scale point). As part of preregistered data quality processing, we removed background sessions and verified there were no overlapping sessions after preprocessing, before proceeding to the planned analyses. No additional exclusion criteria beyond those preregistered were introduced.

Table 3. Summary of deviations from preregistration

Study Aspect	Preregistered	Actual	Justification for Deviation
Data collection	All participants sourced from PureProfile	Participants sourced from both PureProfile and Prolific	Exhausted PureProfile participant pool before reaching required sample size
Data collection	Screening sample would be nationally representative by ethnicity and gender	Approximately 50% of screening was done using quotas for national representativeness by ethnicity and gender; all subsequent sampling used convenience sampling with no quotas	Exhausted participant pools of smaller demographic categories on both Prolific and PureProfile before reaching required sample size
Data collection	Sample consists of participants aged 18–30	Sample consists of participants aged 18–40	(1) Unable to recruit enough participants in the US aged 18–30
Data collection	To qualify, $\geq 75\%$ of a participant's total gaming must take place on platforms included in the study (Xbox, Steam, Nintendo Switch)	To qualify, $\geq 50\%$ of a participant's total gaming must take place on platforms included in the study (Xbox, Steam, Nintendo Switch)	Low rates of study qualification at 75% threshold, in large part due to substantial uncaptured Playstation play
Data collection	Qualification contingent upon valid digital trace data within last 7 days	Qualification contingent upon valid digital trace data within last 14 days	Feedback from participants indicating that play during a 7-day period was subject to too many fluctuations (e.g., a busy workweek)
Data collection	Daily surveys sent at 7pm local time	Daily surveys sent at 2pm local time	Feedback from participants indicating that evening plans often interfered with survey completion and thus adversely affected response rate
Analysis	Data would be imputed for all participants given a 50% overall response rate	Data imputed for only participants with an individual 50% response rate	Imputing values for participants with 50–97% missing data is poorly justified; results from the preregistered analysis with imputation for all participants are reported in the Appendix (Sensitivity Analysis 5) and do not meaningfully differ from the main analysis

Imputation

We used multiple imputation by chained equations (MICE) with predictive mean matching (PMM) to handle missing data. Missing data were imputed for daily need satisfaction/frustration items (BPNSFS, BANGS) and displacement measures (an average of 22.5% missing cells across 97.1% of participants with at least one wave of missing data). Digital trace data were not imputed because tracking was continuous and automatic; within-platform, missing data represent recorded absence of play.

Following the two-stage protocol from Von Hippel (2020) based on fraction of missing information, we used 27 imputations. For all variables, imputed distributions closely overlapped with the observed data (see Appendix Figure A0.1). Models were fit separately to each imputed dataset, and estimates were pooled across imputations using Rubin's rules as implemented in the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011). For comparison, complete case analyses are reported in the Appendix (Sensitivity Analysis 4); results do not meaningfully differ from the imputed analyses.

Deviations from Preregistration

We made several deviations from our preregistration to ensure we could recruit enough high-quality participants to meet our sample size goals. In our view, none are so severe enough to threaten the validity of the study. Deviations are summarized in Table 3.

Positive Controls

As specified in the preregistration, we assessed two positive controls designed to assess whether our data were capable of addressing our stated hypotheses. Both passed: self-reported playtime correlated positively with logged playtime ($r = 0.28$, 95% CI [0.26, 0.30]); and after preprocessing (e.g., to remove background sessions), there were

no overlapping sessions. We therefore proceeded with the planned analyses.

Analysis Approach

We tested each hypothesis using multilevel within-between regression models estimated with *glmmTMB* (Brooks et al., 2017). Focal predictors were within-person mean-centered, with 30-day person means included to separate day-level from 30-day aggregate associations. All models included random intercepts and AR(1) autocorrelation structures; H1 and H3 additionally included random slopes for day-level predictors, while H2 used random intercepts only due to convergence issues with the binary outcome. No demographic covariates were included, as the within-between specification controls for all time-invariant individual differences.

This approach isolates day-to-day dynamics: day-level coefficients estimate how much a person's outcome deviates from their own 30-day average when their predictor deviates from their own 30-day average. For example, H1's day-level coefficient answers: 'On days when individuals experience better game need satisfaction than their typical level, do they report higher global need satisfaction than their typical level?' The non-focal 30-day aggregate coefficients capture whether people with generally higher predictor levels also have generally higher outcomes across the study period. Random effects account for stable individual differences (e.g., personality, gaming preferences), and the AR(1) term models temporal autocorrelation in daily data. This specification does not adjust for time-varying confounds; estimates should be interpreted as associations rather than causal effects.

Study 1 Results: Confirmatory

We present visualizations for each hypothesis test in turn; all key estimates are summarized Table 4.

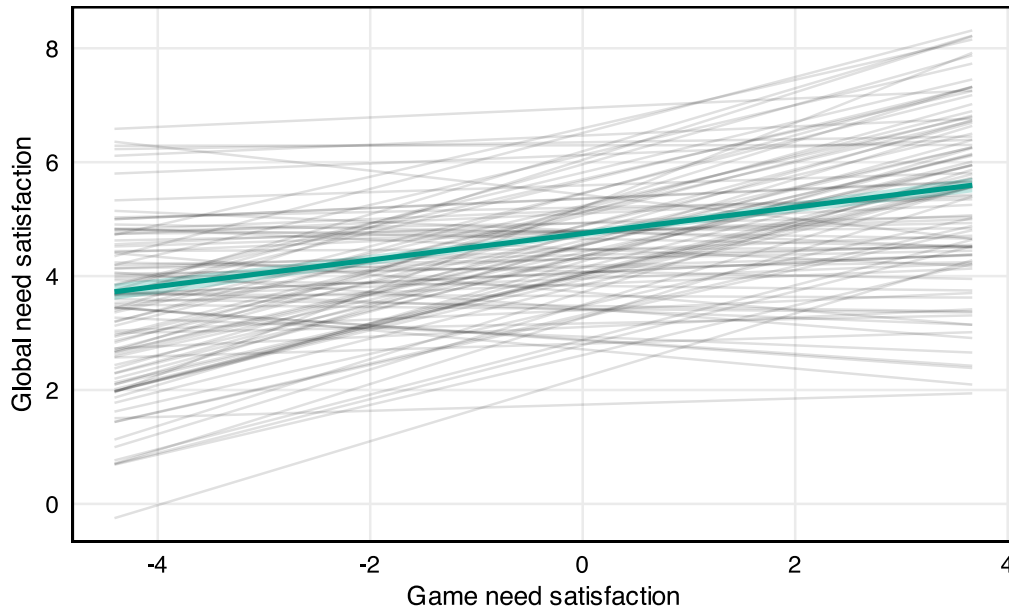


Figure 2. Estimated global need satisfaction as a function of need satisfaction in games. Individual trajectories shown as gray lines, population-level association shown as blue line with 95% confidence ribbon.

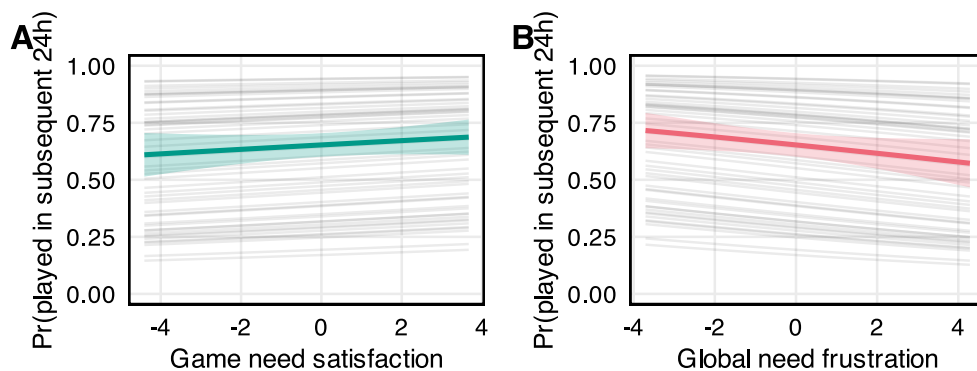


Figure 3. Estimated probability of playing in subsequent 24 hours. (A) As a function of need satisfaction in games (H2a). (B) As a function of global need frustration (H2b). Individual trajectories shown as gray lines, population-level associations shown with 95% confidence ribbons.

H1. Greater in-game need satisfaction is associated with greater global need satisfaction

Results strongly support H1 (Figure 2). At the day level, game need satisfaction was positively associated with global need satisfaction ($\beta = 0.24$ [95% CI: 0.21, 0.27], $p < .001$). On days when participants experienced game need satisfaction 1 scale point (1–7 scale) above their personal 30-day average, they reported global need satisfaction 0.24 units above their personal 30-day average.

At the 30-day aggregate level, which was not the focus of our hypothesis about day-to-day dynamics, the association ($\beta = 0.86$ [95% CI: 0.77, 0.95], $p < .001$) was strong, indicating strong between-individual differences.

H2. Situational need satisfaction is positively associated with the likelihood of playing in the period after survey completion (H2a), while global need frustration is negatively associated (H2b)

We tested H2a and H2b using a single multilevel within-between logistic regression, where in-game need satisfaction and global need frustration (each within- and between-person centered) predicted a binary variable whether any play happened in the 24-hour period after diary survey completion.

Results support neither H2a or H2b: at the day level, experiencing neither 1 point higher game need satisfaction ($\beta = 0.04$ [95% CI: -0.03 , 0.12], $p = 0.277$) nor 1 point higher global need frustration ($\beta = -0.08$ [95% CI: -0.16 , 0.00], $p = 0.062$) than usual on a 1-point scale showed

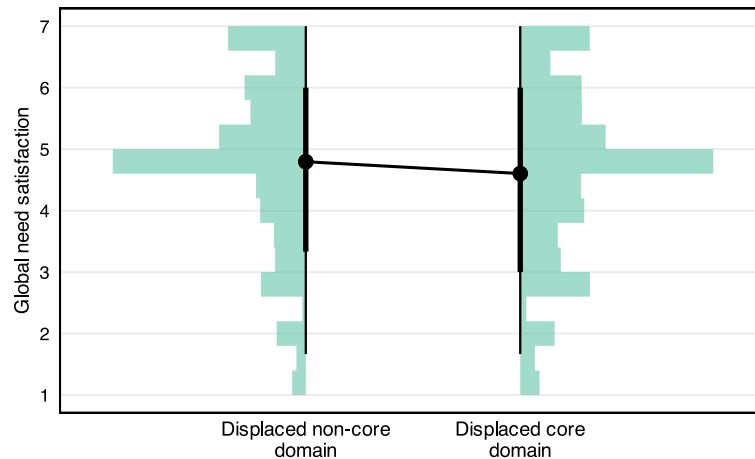


Figure 4. Global need satisfaction when gaming was reported to displace vs. not displace a core life domain. Plot shows distribution (histogram) and mean with 80% and 95% quantile intervals.

meaningful associations with the likelihood of subsequent play (see Figure 3).

We conducted a wide range of sensitivity analyses providing convergent conclusions: key estimates for gaming need satisfaction (game NS) and global need frustration (global NF) remain indistinguishable from 0 in models that:

- use subsequent 6 hours (game NS: $\beta = 0.04$; global NF: $\beta = -0.01$) or 12 hours (game NS: $\beta = 0.04$; global NF: $\beta = -0.02$) as the outcome, instead of 24 hours (Sensitivity Analysis 1)
- use alternative random slopes specifications (game NS: $\beta = 0.04$; global NF: $\beta = -0.06$) (Sensitivity Analysis 2)
- use a count model of minutes played in the subsequent 24 hours instead of binary play/no-play (game NS: $\beta = 0.04$; global NF: $\beta = -0.08$) (Sensitivity Analysis 3)
- use complete case data instead of imputed data (game NS: $\beta = 0.04$; global NF: $\beta = -0.08$) (Sensitivity Analysis 4)
- impute data from the full eligible sample instead of the analytic sample (game NS: $\beta = 0.04$; global NF: $\beta = -0.08$) (Sensitivity Analysis 5)
- include an interaction between gaming need satisfaction and global need frustration (game NS: $\beta = 0.04$; global NF: $\beta = -0.08$; game NS * global NF: $\beta = 0.04$) (Sensitivity Analysis 6)
- use a spline term for gaming need satisfaction and global need frustration, instead of a linear term (Sensitivity Analysis 7)
- enter each individual need (autonomy, competence, relatedness) as predictors instead of composite need satisfaction or frustration (Sensitivity Analysis 8)

The 30-day aggregate associations (game need satisfaction: $\beta = 0.04$ [95% CI: $-0.29, 0.37$], $p = 0.799$; global need frustration: $\beta = 0.07$ [95% CI: $-0.20, 0.34$], $p = 0.615$) similarly indicate no relationship across individuals; these

are reported as exploratory and unrelated to the focal hypotheses about short-term behavioral dynamics.

In short, results consistently fail to detect an association between situational need satisfaction or global need frustration and subsequent play behavior.

H3. When gaming displaces a core life domain, global need satisfaction will be lower

Participants reported what activity their gaming session displaced 14,041 times across the study. In 5,647 cases (40.2%), gaming displaced a core life domain: sleep, eating, or fitness ($n = 2,038$), social engagements ($n = 302$), work or school ($n = 1,613$), or caretaking ($n = 35$). Gaming most commonly displaced non-core activities such as other digital media use ($n = 4,211$) and other leisure activities ($n = 1,297$).

Results provide very weak support for H3 ($\beta = -0.06$ [95% CI: $-0.10, -0.01$], $p = 0.021$). When gaming displaced a core life domain rather than a non-core activity, participants reported global need satisfaction -0.06 units lower on average. On a 7-point scale, this difference is extremely small, and the distributions of global need satisfaction when gaming displaced core vs. non-core domains are nearly identical (Figure 4).

An exploratory analysis (Appendix Sensitivity Analysis 10) examined whether this relationship differed for specific displaced life domains. Results showed that need satisfaction was lower when gaming displaced work/school responsibilities and sleep/eating/fitness, but—contrary to expectations—tended to be higher when gaming displaced social engagements or caretaking. We return to this in the discussion.

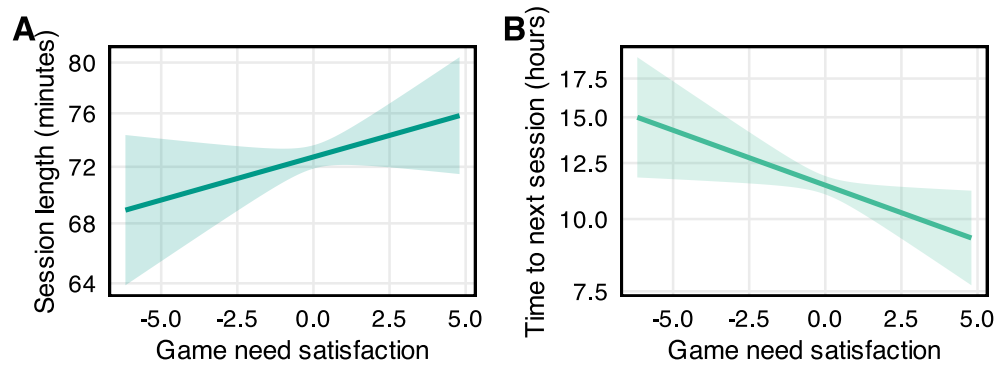


Figure 5. Relationship between session-to-session fluctuations in need satisfaction and play behavior in PowerWash Simulator. (A) Session length. (B) Time to next session. Shaded regions show 95% confidence intervals.

Table 4. Summary of main hypothesis tests (H1-H3)

	Parameter	Estimate	SE	Statistic	p
H1: game NS → global NS	Game need satisfaction (within)	0.238	0.017	14.294 (t)	<.001
H2: game NS + global NF → play	Game need frustration	0.042	0.038	1.088 (z)	0.277
H2: game NS + global NF → play	Global need frustration	-0.080	0.043	-1.864 (z)	0.062
H3: displaced core → global NS	Game need frustration	-0.056	0.024	-2.316 (t)	0.021

Study 2: Exploratory Evidence from PowerWash Simulator

Study 2 Method

To assess whether our findings generalize beyond the Open Play dataset, we conducted a secondary analysis of data from *PowerWash Simulator* (PWS) (Vuorre, Magnusson, et al., 2023). PWS is a first-person simulation game where players use pressure washers to clean various objects. The PWS dataset complements the Open Play data because it is highly granular: players were prompted during gameplay to rate their experiences of autonomy, competence, focus, wellbeing, immersion, and enjoyment on 0-100 scales, on average once every 10 minutes throughout a play session. We linked these ratings to play behavior extracted from game logs.

The original study procedures were granted ethical approval by Oxford University’s Central University Research Ethics Committee (SSH_OII_CIA_21_011).

Participants

The characteristics of the full sample of 11,080 players in the PWS dataset are described in Vuorre, Magnusson, et al. (2023); here, we briefly describe the subset of data relevant to our questions. All participants were over 18 years old, provided informed consent, answered at least one mood question, and did not request their data to be deleted. The median age was 27 (19, 40; 1st and 9th deciles), and the

four most frequent gender responses were Male (4,537, 52.2%), Female (2,675, 30.8%), Non-binary (723, 8.3%), and Transgender (326, 3.7%). Participants were resident in 39 countries, with the USA (4,917, 56.5%), UK (840, 9.7%), Canada (448, 5.2%), and Germany (390, 4.5%) being the most represented. Recruitment happened in multiple waves through multiple avenues inside and outside of the game. Study participation was incentivized through cosmetic in-game rewards (e.g., item skins).

Measures

Play sessions were defined as continuous periods of activity separated by gaps in engagement of at least 30 minutes, yielding 101,602 sessions across 8,969 players. Based on the session timestamps, we calculated two behavioral outcomes: session length (minutes) and session gap (hours; defined as the end timestamp of the previous session and the start timestamp of the subsequent one).

Need satisfaction was measured via two in-game prompts on a visual analogue scale from 0 to 100: an autonomy item “Just now, I was doing the things I really wanted to in Powerwash Simulator” and a competence item “Just now, I felt competent playing PowerWash Simulator”, each with visual analogue scale endpoints “Not at all” and “As much as possible”. We converted each observation to a 1–10 scale for interpretability. For each session, we took the mean of all autonomy and competence ratings to generate a single need satisfaction indicator (analogously to Study 1) and decomposed it into within- and between-person components.

Analysis Approach

Analogously to study 1, we estimated the relationship between need satisfaction and outcomes (session length, session gap) using linear mixed effects models, with random intercepts and slopes for each participant. Outcomes were log-transformed due to heavily right-skewed distributions. Following our main analysis approach, we decomposed need satisfaction predictors into within- and between-person components and controlled for previous session length and session gap to isolate need satisfaction effects.

Study 2 Results: Exploratory

Results are shown in Figure 5. At the session level, game need satisfaction showed a very weak association with session length ($\beta = 0.009$, 95% CI [-0.003, 0.021], $p = 0.159$). Panel A illustrates that when players experienced higher need satisfaction than their personal average, they did not play meaningfully longer: if a player who typically reported need satisfaction of 1 instead reported a 10, their expected change in session length would be only 5.9 minutes [95% CI -1.4, 14.2].

Similarly, game need satisfaction showed a weak association with time to next session ($\beta = -0.044$, 95% CI [-0.082, -0.005], $p = 0.025$). Panel B shows that if a player who typically reported need satisfaction of 1 instead reported a 10, their next session would begin -3.7 hours [95% CI -5.6, -0.9] sooner than usual. While this association is significant, given that typical session-to-session deviations in need satisfaction are much smaller (within-person SD = 0.71 points), we interpret the practical relevance to behavior as small. It remains an open question how these motivational factors may influence collective human behavior on the games or games platform levels of analysis.

Broadly, results therefore converge with Study 1: Despite examining 101,602 sessions from 8,969 players in a different game using different measures, the pattern of weak behavioral associations replicated. Full model outputs are provided in the Appendix (Table A0.4).

Discussion

Across Study 1 and Study 2, our findings reveal a consistent pattern: basic psychological needs—whether satisfied in games or frustrated in daily life—show weak or null relationships with subsequent gaming behavior. This apparent disconnect between self-reported and behavioral outcomes has important implications. Self-determination theory, particularly as applied to games, has been extensively validated using self-report measures. Players who report higher need satisfaction also report greater enjoyment, stronger intentions to continue playing, and better wellbeing outcomes (Tyack & Mekler, 2020; Adinolf & Türkay (2019); Oliver et al. (2016); Tamborini et al. (2011); Formosa et al. (2022); Tyack et al. (2020)]. Our results do not challenge these relationships. Rather, they suggest that for individual players, the pathway from needs to actual behavior may be substantially weaker or more complex than the pathway from needs to self-reported experiences and intentions.

Our findings are not the first to report weak links between basic needs and gaming engagement as measured by digital trace data. Motivation was only very weakly associated with total engagement in *League of Legends* (Brühlmann et al., 2020). Competence satisfaction did not meaningfully relate to voluntary engagement in a custom RPG (Kao et al., 2024), and satisfaction of all three needs was only very weakly related to playtime in *Animal Crossing: New Horizons* and *Plants vs Zombies: Battle for Neighborville* over a 2-week timescale ($r = .07$, likely too small to be practically significant) (Johannes et al., 2021).

We add to these findings with more comprehensive trace data (spanning 5 platforms in Study 1 and detailed single-game records in Study 2) and higher-frequency wellbeing data. Given accumulating weak links between needs and behavior, we suggest several paths forward.

Implications for the BANG model

Only one of BANG's predictions was supported (H1/B6: game needs are positively associated with global needs), consistent with prior literature (Allen & Anderson, 2018; Ballou, Denisova, et al., 2024) and the proposed hierarchical structure at the core of SDT (Vallerand, 1997). However, the behavioral predictions fared poorly: neither in-game positive experiences nor deficits in life in general meaningfully related to subsequent play, and self-reported displacement was negligibly related to wellbeing. All in all, BANG hypotheses B5, B8, and B9 were unsupported in our data.

Null results for theoretical predictions can generally be attributed to (1) lack of statistical power, (2) validity issues (e.g., poor design, poor measures), (3) incorrect auxiliary hypotheses, or (4) theory failure (Meehl, 1990). We argue that our study is reasonably well-powered (see Ballou, Földes, Hakman, et al., 2025 for simulated sensitivity analyses), and with the exception of H3 whose "hypothetical displacement" measure has obvious flaws (see Limitations), uses valid measures—in particular, because we observe real-world behavior.

We endeavored to test one of the most prominent auxiliary hypotheses present, namely the auxiliary of correct timescale, by comparing 6-hour, 12-hour, and 24-hour time periods, and by triangulating using the PowerWash Simulator dataset, wherein need-related experiences are captured within the session itself. However, none were able to find meaningful support for the behavioral predictions.

We therefore interpret our results as evidence against certain BANG predictions, necessitating model updating. From a metascientific perspective, model updating after falsification is central to iterative model calibration and theory modulation (Meehl, 1990), in which constructs are sharpened, measurement improved, and boundary conditions more precisely articulated. Updating BANG requires identifying *when* and *why* need-related processes do and do not relate to behavioral engagement.

A wholesale revision of BANG is beyond the scope of the current paper, but our results suggest follow-up investigation should be limited to targeted probes aimed at determining whether the null results here reflect (i) temporal misalignment, for example, it may be that need satisfaction updates expectations on a timescale longer than 24 hours, Ballou & Deterding (2023a)]; (ii) boundary conditions (for example, if need-behavior links emerge only for specific players, games, or contexts with low constraint and weak habitual control); or (iii) competing processes (for example, if habits, reinforcement histories, and situational affordances dominate short-term behavior, leaving needs to shape preferences rather than actions). Critically, if behavioral effects remain absent under conditions designed to maximise their detectability, BANG's

behavioral claims should be revised or removed rather than further insulated.

Alternative behavioral frameworks

The modest associations we found between need experiences and subsequent play behavior suggest that basic psychological needs may not be the primary drivers of short-term gaming engagement. In light of this, we suggest player experience research consider other theoretical frameworks that might provide better or complementary explanations for short-term gaming engagement. We are aware of at least three such frameworks.

Behaviorist and reinforcement-learning accounts emphasize the power of recent rewards and environmental cues, rather than subjective motives, in sustaining behavior (Niv, 2009; Skinner, 1965). Recent work has expanded and adapted these predictions for the digital media domain (James & Tunney, 2017b, 2017a; Norwood & Przybylski, 2025). Under such models, a primary cause of players re-engaging is that the behavior has been reliably reinforced, not because they recently felt more autonomy, competence, or relatedness.

Habit theory similarly predicts minimal coupling between momentary experiences and action. With sufficient repetition in stable contexts, gaming becomes cue-triggered and automatic, guided by procedural memory rather than conscious motivational states (Ouellette & Wood, 1998; Wood & Rünger, 2016). If players typically launch games at particular times or in response to specific cues, need fluctuations may exert little incremental influence over behavior.

A third possibility is regulatory cessation. In homeostatic and cybernetic models, behavior is energized by need- or goal-discrepancies and should weaken once these are reduced; highly satisfying engagement may therefore decrease the likelihood of immediate re-engagement (Carver & Scheier, 2001; Hull, 1943; Toates, 1986). Self-determination theory explicitly rejects this logic for psychological needs, arguing that need satisfaction does not produce satiation or motivational decline and may instead sustain intrinsic motivation (Sheldon & Gunz, 2009). However, SDT evidence has primarily relied on self-reported motivation rather than observed behavioral continuation, potentially obscuring homeostatic or satiation-like dynamics that operate at the level of action. In games research, where engagement unfolds as repeated consumption, such regulatory processes may better account for short-term disengagement following highly satisfying play episodes.

Each of these perspectives aligns with broader evidence that subjective intentions and experiences often predict real-world actions only weakly because behavior is multiply determined and heavily constrained by situational affordances (Sheeran & Webb, 2016). For researchers, our findings therefore suggest that comprehensive models of gaming behavior may need to incorporate reinforcement histories, habits, and regulatory processes alongside need-based motivations (Sharpe et al., 2025). For game developers, they suggest that relying on experiential metrics (e.g., ‘fun’, satisfaction surveys) may provide an incom-

plete picture of what sustains engagement. For parents and clinicians, they suggest that efforts to promote healthier play patterns may benefit from structural interventions (e.g., increasing friction, modifying environment to reduce contextual cues) rather than focusing on enhancing need fulfillment.

The value of open behavioral data

The introduction to this paper outlined three key limitations in gaming research: lack of researcher access to industry data, temporal mismatch between trace data and surveys, and weak theoretical frameworks. Our study addressed all three by negotiating multi-platform access, implementing daily diaries, and testing theory-driven predictions. Yet the clearest contribution may be demonstrating what becomes visible when self-report is paired with comprehensive behavioral records.

Self-report measures of play behavior commonly correlates with intrinsic motivation, and thereby higher engagement (Kosa & Uysal, 2024; Neys et al., 2014). The trace data reveal a different picture. This disconnect is not unique to SDT or gaming; intention-behavior gaps are well-documented across health behaviors, environmental actions, and consumer choices (Sheeran & Webb, 2016). Whether or not the underlying reasons are shared across these domains and media use, intention-behavior gaps are particularly consequential in a field where theoretical claims increasingly concern behavior, such as how much people play, when they play, what motivates them to start or stop.

The broader lesson extends beyond SDT. As gaming research matures beyond simple quantity-based approaches (Ballou, Hakman, et al., 2025), theories must be validated against behavioral outcomes, not just self-reported proxies. Open player behavior data, sourced through a mix of player-led data sharing infrastructure, industry partnerships, and other mechanisms, is essential for this work.

There are, however, practical barriers to making such behavioral evidence routine. Privacy and re-identification risks are non-trivial for high-resolution digital trace data, particularly when combined with survey responses, and these risks create understandable reluctance among both participants and data holders (Rocher et al., 2019). Industry incentives also rarely align with open scientific practices: the most informative behavioral data are often commercially sensitive, operationally costly to extract, and legally complex to share across jurisdictions. Methodologically, the field also lacks shared standards for defining sessions, handling idle time, linking multi-platform identities, and documenting preprocessing decisions—each of which can meaningfully affect substantive conclusions.

We therefore advocate for multi-platform solutions, mixing both open source and, where possible with high transparency standards, industry collaborations. Multi-platform coverage matters substantively because platform ecosystems structure when and how people play. Different platforms afford different play contexts (e.g., portable vs. fixed-location play, solitary vs. social defaults, friction to launch, and typical session cadence), and these affor-

dances can shift the distribution of sessions across the day and week. When studies observe only a single platform, they risk misclassifying a person's true "non-play" periods (e.g., apparent disengagement on one platform may simply reflect switching to another), attenuating within-person associations and obscuring displacement dynamics. Single-platform datasets also risk overgeneralizing from idiosyncratic platform cultures and technical constraints (such as background processes, suspend/resume behavior, or account sharing) that can inflate or distort behavioral measures.

Limitations and Future Directions

Several limitations qualify the interpretation of the present findings. First, although our analyses focus on within-person associations, these estimates should not be interpreted as causal effects (Rohrer & Murayama, 2021). Even with high-frequency longitudinal measurement, within-person variation does not isolate exogenous change: need satisfaction may covary with unmeasured situational factors (e.g., time availability, fatigue, social context) that independently shape gaming behavior. Our results therefore speak to the strength of empirical coupling between needs and behavior, not to causal necessity or sufficiency.

Second, our test of displacement (H3) relies on a hypothetical counterfactual measure: what participants report they would have done had they not played. This approach is coarse and vulnerable to recall bias, rationalisation, and ambiguity in how respondents interpret "most likely" alternatives. While the measure provides a useful first pass at identifying potentially displaced life domains, it is ill-suited for detecting subtle or cumulative displacement processes and likely attenuates any true effects. More rigorous tests of displacement will require objective time-use data or designs that directly observe trade-offs between activities.

Third, the behavioral outcomes examined here reflect short-term engagement patterns, such as session length and return latency. Null or weak associations at this timescale do not rule out need-related effects on longer-term outcomes, such as game choice, persistence over months, or disengagement trajectories. Our conclusions are therefore limited to short-term behavioral dynamics and should not be generalized to all forms of gaming involvement.

Fourth, while the Study 1 data represent a substantial advancement in capturing comprehensive multi-platform data, they are nonetheless incomplete: players in our sample may have played games on Playstation, played third-party games on Nintendo, or played on mobile (which, while captured, was not captured in sufficient temporal resolution to inform the hypotheses here). Methods for reliably capturing data from each gaming platform require further development.

Finally, our sample, although purposively sampled for racial and gender diversity, should be understood as consisting of engaged 18–40 year old players willing to share detailed behavioral data and complete intensive surveys, rather than as representative of all players. This selectivity limits generalizability in two ways. First, casual players, younger adolescents, and individuals with mini-

mal or highly irregular play patterns are underrepresented. Second, highly engaged players' behavior may differ systematically from those among less engaged populations (e.g., more routinized or more highly habit-driven). The weak need–behavior associations observed here may not generalize to all player groups, nor do they preclude stronger effects in populations with greater variability in motivation or fewer structural constraints.

Together, these limitations suggest that the present findings should be interpreted as strong evidence against large, general, short-term behavioral effects of need satisfaction among engaged adult players, rather than as definitive evidence against any role for psychological needs in shaping gaming behavior more broadly.

Data Availability

All data, materials, and code related to the dataset and this manuscript are available under CC0 at <https://doi.org/10.5281/zenodo.18352505>.

Funding

This research was supported by the UK Economic and Social Research Council (ES/W012626/1 and ES/Y010736/1). AP was supported by the Huo Family Foundation.

Conflicts of Interest

The authors declare no competing financial, intellectual, or institutional interests relevant to this research. The disclosures below are provided in the interest of full transparency.

All members of the research team have worked on scientific projects funded by government and charitable grants that used data from tech companies provided under a data-sharing agreement. No authors have received funding or compensation from the tech companies or other industries connected to the work presented here.

MV has provided in-kind consultations and served as a nonpaid panel member for Meta and K-Games. AKP has served in advisory or expert roles for the Sync Digital Wellbeing Program (2022–2024), the Google Expert Advisory on Youth and Technology (2025), the OpenAI Expert Council on Well-Being 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.

Data-sharing partners had no role in the design, analysis, or publication of results.

References

- Aalbers, G., vanden Abeele, M. M. P., Hendrickson, A. T., de Marez, L., & Keijsers, L. (2021). Caught in the moment: Are there person-specific associations between momentary procrastination and passively measured smartphone use? *Mobile Media & Commu-*

- nication, 10(1), 205015792199389. <https://doi.org/10.1177/2050157921993896>
- Adinolf, S., & Türkyay, S. (2019). Differences in player experiences of need satisfaction across four games. *Proceedings of DiGRA 2019*, 12.
- Allen, J. J., & Anderson, C. A. (2018). Satisfaction and frustration of basic psychological needs in the real world and in video games predict internet gaming disorder scores and well-being. *Computers in Human Behavior*, 84, 220–229. <https://doi.org/10.1016/j.chb.2018.02.034>
- Ballou, N. (2023). A manifesto for more productive psychological games research. *Games: Research and Practice*, 1(1), 1–26. <https://doi.org/10.1145/3582929>
- Ballou, N., Denisova, A., Ryan, R., Rigby, C. S., & Deterding, S. (2024). The basic needs in games scale (BANGS): A new tool for investigating positive and negative video game experiences. *International Journal of Human-Computer Studies*, 188, 103289. <https://doi.org/10.1016/j.ijhcs.2024.103289>
- Ballou, N., & Deterding, S. (2023a). “I just wanted to get it over and done with”: A grounded theory of psychological need frustration in video games. *The Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '23*, 382. <https://doi.org/10.1145/3611028>
- Ballou, N., & Deterding, S. (2023b). *The basic needs in games (BANG) model of video game play and mental health* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/6vedg>
- Ballou, N., & Deterding, S. (2024). The basic needs in games model of video game play and mental health. *Interacting with Computers*, iwae042. <https://doi.org/10.1093/iwc/iwae042>
- Ballou, N., Deterding, S., Iacovides, I., & Helsby, L. (2022). Do people use games to compensate for psychological needs during crises? A mixed-methods study of gaming during COVID-19 lockdowns. In S. Barbosa, C. Lampe, C. Appert, D. A. Shamma, S. Drucker, J. Williamson, & K. Yatani (Eds.), *CHI '22* (pp. 1–15). ACM Press. <https://doi.org/10.1145/3491102.3501858>
- Ballou, N., Földes, T. A., Hakman, T., Vuorre, M., Magnusson, K., & Przybylski, A. K. (2025). *Psychological wellbeing, sleep, and video gaming: Analyses of comprehensive digital traces [stage 1 programmatic registered report]*. PsyArXiv. https://doi.org/10.31234/osf.io/kvqdy_v1
- Ballou, N., Földes, T. A., Vuorre, M., Hakman, T., Magnusson, K., & Przybylski, A. K. (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, N., Hakman, T., Vuorre, M., Magnusson, K., & Przybylski, A. K. (2024). How do video games affect mental health? A narrative review of 13 proposed mechanisms. *Technology, Mind, and Behavior*, in press. <https://doi.org/10.1037/tmb0000152>
- Ballou, N., Hakman, T., Vuorre, M., Magnusson, K., & Przybylski, A. K. (2025). How do video games affect mental health? A narrative review of 13 proposed mechanisms. *Technology, Mind, and Behavior*, 6(2), 1–21. <https://doi.org/10.1037/tmb0000152>
- Ballou, N., Sewall, C. J. R., Ratcliffe, J., Zendle, D., Tokarchuk, L., & Deterding, S. (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>
- Ballou, N., Vuorre, M., Hakman, T., & Przybylski, A. K. (2025). Perceived value of video games, but not hours played, predicts mental well-being in casual adult nintendo players. *Royal Society Open Science*, 12, 241174. <https://doi.org/10.1098/rsos.241174>
- Bender, P. K., & Gentile, D. A. (2019). Internet gaming disorder: Relations between needs satisfaction in-game and in life in general. *Psychology of Popular Media Culture*, 9(2), 266–278. <https://doi.org/10.1037/ppm0000227>
- Bradt, L., Vermote, B., Zaman, B., Vansteenkiste, M., Van De Castele, M., & Soenens, B. (2024). Are video games and school conflictual or complementary contexts for affording psychological need fulfillment? Implications for adolescents’ problematic gaming and school adjustment. *Interacting with Computers*, iwae020. <https://doi.org/10.1093/iwc/iwae020>
- Brooks, M. E., Kristensen, K., van Benthem, K. J., Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., & Bolker, B. M. (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *The R Journal*, 9(2), 378–400. <https://journal.r-project.org/archive/2017/RJ-2017-066/index.html>
- Brühlmann, F., Baumgartner, P., Wallner, G., Kriglstein, S., & Mekler, E. D. (2020). Motivational profiling of league of legends players. *Frontiers in Psychology*, 11, 1307. <https://doi.org/10.3389/fpsyg.2020.01307>
- Büchi, M. (2024). Digital well-being theory and research. *New Media & Society*, 26(1), 172–189. <https://doi.org/10.1177/14614448211056851>
- Carver, C. S., & Scheier, M. F. (2001). *On the self-regulation of behavior* (First paperback edition). Cambridge University Press.
- Chang, I.-C., Liu, C.-C., & Chen, K. (2014). The effects of hedonic/utilitarian expectations and social influence on continuance intention to play online games. *Internet Research*, 24(1), 21–45. <https://doi.org/10.1108/IntR-02-2012-0025>
- Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, 39(2), 216–236. <https://doi.org/10.1007/s11031-014-9450-1>
- Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer US. <https://doi.org/10.1007/978-1-4899-2271-7>

- Domahidi, E., Breuer, J., Kowert, R., Festl, R., & Quandt, T. (2018). A longitudinal analysis of gaming- and non-gaming-related friendships and social support among social online game players. *Media Psychology, 21*(2), 288–307. <https://doi.org/10.1080/15213269.2016.1257393>
- Drummond, A., & Sauer, J. D. (2020). Timesplitters: Playing video games before (but not after) school on weekdays is associated with poorer adolescent academic performance. A test of competing theoretical accounts. *Computers & Education, 144*, 103704. <https://doi.org/10.1016/j.compedu.2019.103704>
- El-Nasr, M. S., Nguyen, T.-H. D., Canossa, A., & Drachen, A. (2021). *Game data science* (First edition). Oxford University Press.
- Entertainment Software Association. (2024). *2024 essential facts about the u.s. Video game industry*. Entertainment Software Association. <https://www.theesa.com/wp-content/uploads/2024/05/Essential-Facts-2024-FINAL.pdf>
- Ernala, S. K., Burke, M., Leavitt, A., & Ellison, N. B. (2020). How well do people report time spent on facebook?: An evaluation of established survey questions with recommendations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14. <https://doi.org/10.1145/3313831.3376435>
- Formosa, J., Johnson, D., Türkay, S., & Mandryk, R. L. (2022). Need satisfaction, passion and wellbeing effects of videogame play prior to and during the COVID-19 pandemic. *Computers in Human Behavior, 131*, 107232. <https://doi.org/10.1016/j.chb.2022.107232>
- Granic, I., Lobel, A., & Engels, R. C. M. E. (2014). The benefits of playing video games. *American Psychologist, 69*(1), 66–78. <https://doi.org/10.1037/A0034857>
- Hull, C. L. (1943). *Principles of behavior an introduction to behavior theory*. Appleton-Century-Crofts.
- James, R. J. E., & Tunney, R. J. (2017a). The need for a behavioural analysis of behavioural addictions. *Clinical Psychology Review, 52*, 69–76. <https://doi.org/10.1016/j.cpr.2016.11.010>
- James, R. J. E., & Tunney, R. J. (2017b). The relationship between gaming disorder and addiction requires a behavioral analysis: Commentary on: Scholars' open debate paper on the world health organization ICD-11 gaming disorder proposal (aarseth et al.). *Journal of Behavioral Addictions, 6*(3), 306–309. <https://doi.org/10.1556/2006.6.2017.045>
- Johannes, N., Masur, P. K., Vuorre, M., & Przybylski, A. K. (2024). How should we investigate variation in the relation between social media and well-being? *Meta-Psychology, 8*, 2022.3322. <https://doi.org/10.15626/MP.2022.3322>
- Johannes, N., Vuorre, M., & Przybylski, A. K. (2021). Video game play is positively correlated with well-being. *Royal Society Open Science, 8*(2), rsos.202049, 202049. <https://doi.org/10.1098/rsos.202049>
- Kahn, A. S., Ratan, R., & Williams, D. (2014). Why we distort in self-report: Predictors of self-report errors in video game play. *Journal of Computer-Mediated Communication, 19*(4), 1010–1023. <https://doi.org/10.1111/jcc4.12056>
- Kao, D., Ballou, N., Gerling, K., Breitsohl, H., & Deterding, S. (2024). How does juicy game feedback motivate? Testing curiosity, competence, and effectance. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–16. <https://doi.org/10.1145/3613904.3642656>
- King, D. L., Gradisar, M., Drummond, A., Lovato, N., Wessel, J., Micic, G., Douglas, P., & Delfabbro, P. (2013). The impact of prolonged violent video-gaming on adolescent sleep: An experimental study. *Journal of Sleep Research, 22*(2), 137–143. <https://doi.org/10.1111/j.1365-2869.2012.01060.x>
- Kocak Alan, A., Tumer Kabadayi, E., & Cavdar Aksoy, N. (2022). Replaying online games for flow experience and outcome expectations: An exploratory study for the moderating role of external locus of control based on turkish gamers' evaluations. *Entertainment Computing, 40*, 100460. <https://doi.org/10.1016/j.entcom.2021.100460>
- Kosa, M., & Uysal, A. (2024). Exploration of novelty as part of the player experience of need satisfaction in games. *Interacting with Computers, iwae006*. <https://doi.org/10.1093/iwc/iwae006>
- Larose, R., Mastro, D., & Eastin, M. S. (2001). Understanding internet usage: A social-cognitive approach to uses and gratifications. *Social Science Computer Review, 19*(4), 395–413. <https://doi.org/10.1177/089443930101900401>
- Larrieu, M., Fombouchet, Y., Billieux, J., & Decamps, G. (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*, 107824. <https://doi.org/10.1016/j.chb.2023.107824>
- Luhmann, M., Krasko, J., & Terwiel, S. (2021). Subjective well-being as a dynamic construct. In *The handbook of personality dynamics and processes* (pp. 1231–1249). Elsevier. <https://doi.org/10.1016/B978-0-12-813995-0.00048-0>
- Martela, F., & Ryan, R. M. (2024). Assessing autonomy, competence, and relatedness briefly: Validating single-item scales for basic psychological need satisfaction. *European Journal of Psychological Assessment, 1015–5759/a000846*. <https://doi.org/10.1027/1015-5759/a000846>
- Meehl, P. E. (1990). Why summaries of research on psychological theories are often uninterpretable. *Psychological Reports, 66*, 195–244. <https://doi.org/10.2466/pr0.1990.66.1.195>
- Mills, D. J., Milyavskaya, M., Mettler, J., & Heath, N. L. (2018). Exploring the pull and push underlying problem video game use: A self-determination theory approach. *Personality and Individual Differences, 135*, 176–181. <https://doi.org/10.1016/j.paid.2018.07.007>
- Murayama, K., & Jach, H. (2023). *A critique of motivation constructs to explain higher-order behavior: We should*

- unpack the black box [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/juxkh>
- Neys, J. L. D., Jansz, J., & Tan, E. S. H. (2014). Exploring persistence in gaming: The role of self-determination and social identity. *Computers in Human Behavior*, 37, 196–209. <https://doi.org/10.1016/j.chb.2014.04.047>
- Niv, Y. (2009). Reinforcement learning in the brain. *Journal of Mathematical Psychology*, 53(3), 139–154. <https://doi.org/10.1016/j.jmp.2008.12.005>
- Norwood, S. F., & Przybylski, A. K. (2025). A new lens for understanding how digital technologies facilitate human behaviour. PsyArXiv. https://doi.org/10.31234/osf.io/ztev4_v1
- Ofcom. (2023). *Online nation 2023 report* (p. 106). Ofcom. <https://www.ofcom.org.uk/siteassets/resources/documents/research-and-data/online-research/online-nation/2023/online-nation-2023-report.pdf?v=368355>
- Oliver, M. B., Bowman, N. D., Woolley, J. K., Rogers, R., Sherrick, B. I., & Chung, M.-Y. (2016). Video games as meaningful entertainment experiences. *Psychology of Popular Media Culture*, 5(4), 390–405. <https://doi.org/10.1037/ppm0000066>
- Orben, A. (2022). Digital diet: A 21st century approach to understanding digital technologies and development. *Infant and Child Development*, e2228. <https://doi.org/10.1002/icd.2228>
- Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*, 124(1), 54–74. <https://doi.org/10.1037/0033-2909.124.1.54>
- Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour*, 5, 1535–1547. <https://doi.org/10.1038/s41562-021-01117-5>
- Przybylski, A. K., Rigby, C. S., & Ryan, R. M. (2010). A motivational model of video game engagement. *Review of General Psychology*, 14(2), 154–166. <https://doi.org/10.1037/A0019440>
- Qwen Team. (2025). *Qwen3 technical report [model tag Qwen3:4b-instruct, model ID Oedcdef34593, accessed 1 dec 2025]*. <https://arxiv.org/abs/2505.09388>
- Reer, F., & Quandt, T. (2020). Digital games and well-being: An overview. In R. Kowert (Ed.), *Video games and well-being* (pp. 1–21). Springer International Publishing. https://doi.org/10.1007/978-3-030-32770-5_1
- Rigby, C. S., & Ryan, R. M. (2011). *Glued to games: How video games draw us in and hold us spellbound*. ABC-CLIO.
- Rocher, L., Hendrickx, J. M., & De Montjoye, Y.-A. (2019). Estimating the success of re-identifications in incomplete datasets using generative models. *Nature Communications*, 10(1), 3069. <https://doi.org/10.1038/s41467-019-10933-3>
- Rohrer, J. M., & Murayama, K. (2021). *These are not the effects you are looking for: Causality and the within-/between-person distinction in longitudinal data analysis* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/tg4vj>
- Ryan, R. M. (Ed.). (2023a). *The oxford handbook of self-determination theory* (1st ed.). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780197600047.001.0001>
- Ryan, R. M. (Ed.). (2023b). *The oxford handbook of self-determination theory*. Oxford University Press.
- Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.
- Ryan, R. M., Duineveld, J. J., Domenico, S. I. D., Ryan, W. S., Steward, B. A., & Bradshaw, E. L. (2022). We know this much is (meta-analytically) true: A meta-review of meta-analytic findings evaluating self-determination theory. *Psychological Bulletin*, 148(11-12), 813–842. <https://doi.org/10.1037/bul0000385>
- Sharpe, M., Bowen, M., & Lambiotte, R. (2025). Quantifying digital habits. *EPJ Data Science*, 14(1), 72. <https://doi.org/10.1140/epjds/s13688-025-00581-7>
- Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. *Social and Personality Psychology Compass*, 10(9), 503–518. <https://doi.org/10.1111/spc3.12265>
- Sheldon, K. M., Abad, N., & Hinsch, C. (2011). A two-process view of facebook use and relatedness need-satisfaction: Disconnection drives use, and connection rewards it. *Journal of Personality and Social Psychology*, 100(4), 766–775. <https://doi.org/10.1037/a0022407>
- Sheldon, K. M., & Gunz, A. (2009). Psychological needs as basic motives, not just experiential requirements. *Journal of Personality*, 77(5), 1467–1492. <https://doi.org/10.1111/j.1467-6494.2009.00589.x>
- Siebers, T., Beyens, I., Pouwels, J. L., & Valkenburg, P. M. (2021). *Explaining variation in adolescents' social media-related distraction: The role of social connectivity and disconnectivity factors* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/g6na7>
- Skinner, B. F. (1965). *Science and human behavior*. Free Press.
- Tamborini, R., Grizzard, M., Bowman, N. D., Reinecke, L., Lewis, R. J., & Eden, A. (2011). Media enjoyment as need satisfaction: The contribution of hedonic and nonhedonic needs. *Journal of Communication*, 61(6), 1025–U55. <https://doi.org/10.1111/j.1460-2466.2011.01593.x>
- Toates, F. (1986). *Motivational systems* (1. publ). Cambridge Univ. Press.
- Tyack, A., & Mekler, E. D. (2020). Self-determination theory in HCI games research – current uses and open questions. *CHI*, 21. <https://doi.org/10.1145/3313831.3376723>
- Tyack, A., Wyeth, P., & Johnson, D. (2020). Restorative play: Videogames improve player wellbeing after a need-frustrating event. In R. Bernhaupt, F. Muller, D. Verweij, & J. Andres (Eds.), *Proceedings of the 2020 CHI conference on human factors in computing systems* (p. 15). ACM Press. <https://doi.org/10.1145/3313831.3376332>

- Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. In *Advances in experimental social psychology* (Vol. 29, pp. 271–360). Elsevier. [https://doi.org/10.1016/S0065-2601\(08\)60019-2](https://doi.org/10.1016/S0065-2601(08)60019-2)
- van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in r. *Journal of Statistical Software*, *45*(3), 1–67. <https://doi.org/10.18637/jss.v045.i03>
- Vansteenkiste, M., Ryan, R. M., & Soenens, B. (2020). Basic psychological need theory: Advancements, critical themes, and future directions. *Motivation and Emotion*, *44*(1), 1–31. <https://doi.org/10.1007/s11031-019-09818-1>
- Vella, K., & Johnson, D. (2012). Flourishing and video games. In C. T. Tan (Ed.), *Proceedings of the 8th australasian conference on interactive entertainment: Playing the system* (pp. 1–3). ACM Press. <https://doi.org/10.1145/2336727.2336746>
- Von Hippel, P. T. (2020). How many imputations do you need? A two-stage calculation using a quadratic rule. *Sociological Methods & Research*, *49*(3), 699–718. <https://doi.org/10.1177/0049124117747303>
- Vuorre, M., Ballou, N., Hakman, T., Magnusson, K., & Przybylski, A. K. (2023). *Affective uplift during video game play: A naturalistic case study*. <https://doi.org/10.31234/osf.io/z3ejx>
- Vuorre, M., Johannes, N., Magnusson, K., & Przybylski, A. K. (2022). Time spent playing video games is unlikely to impact well-being. *Royal Society Open Science*, *9*(7), 220411. <https://doi.org/10.1098/rsos.220411>
- Vuorre, M., Magnusson, K., Johannes, N., Butlin, J., & Przybylski, A. K. (2023). An intensive longitudinal dataset of in-game player behaviour and well-being in PowerWash simulator. *Scientific Data*, *10*(1), 622. <https://doi.org/10.1038/s41597-023-02530-3>
- Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual Review of Psychology*, *67*(1), 289–314. <https://doi.org/10.1146/annurev-psych-122414-033417>

A1 Appendix

A1.1 Full Model Outputs

This section provides complete model summaries for the three main hypothesis tests (H1-H3), including all fixed effects, random effects, and autocorrelation parameters.

A1.1.1 H1: *Game need satisfaction is related to global need satisfaction*

Table A1.1. H1: Complete model summary for game NS → global NS

H1: Game NS positively associated with Global NS	
Intercept	4.746
	[4.675, 4.817]
	s.e. = 0.036
	t = 130.605
	p = <0.001
Game need satisfaction (within)	0.232
	[0.204, 0.260]
	s.e. = 0.014
	t = 16.123
	p = <0.001
Game need satisfaction (between)	0.860
	[0.767, 0.953]
	s.e. = 0.047
	t = 18.164
	p = <0.001
SD (Intercept pid)	0.820
SD (game_ns_cw pid)	0.206
Cor (Intercept game_ns_cw pid)	0.044
SD (Observations)	0.792
Num.Obs.	11239
R2 Marg.	0.424
AIC	30324.9
BIC	30390.8
RMSE	0.71

A1.1.2 H2: Need satisfaction and frustration is related to subsequent play

Table A1.2. H2: Complete model summary for game NS + global NF → play

H2: NS & NF associated with likelihood of subsequent play	
Intercept	0.632 CI = [0.404, 0.860] s.e. = 0.116 z = 5.439 p = <0.001
Game need satisfaction (within)	0.042 CI = [-0.033, 0.117] s.e. = 0.038 z = 1.098 p = 0.272
Game need satisfaction (between)	0.057 CI = [-0.273, 0.386] s.e. = 0.168 z = 0.338 p = 0.736
Global need frustration (within)	-0.079 CI = [-0.163, 0.005] s.e. = 0.043 z = -1.847 p = 0.065
Global need frustration (between)	0.080 CI = [-0.190, 0.351] s.e. = 0.138 z = 0.581 p = 0.561
Num.Obs.	10317
AIC	9726.2
BIC	9784.1
Log.Lik.	-4855.107

A1.1.3 H3: Displacing core domains is associated with lower global need satisfaction

Table A1.3. H3: Complete model summary for displaced core → global NS

H3: Displacement of core life domain associated with lower Global NF	
Intercept	4.753
	[4.662, 4.843]
	s.e. = 0.046
	t = 102.550
	p = <0.001
Displaced core domain	-0.048
	[-0.090, -0.007]
	s.e. = 0.021
	t = -2.271
	p = 0.023
SD (Intercept pid)	1.043
SD (displaced_core_domainTRUE pid)	0.054
Cor (Intercept displaced_core_domainTRUE pid)	-0.052
SD (Observations)	0.815
Num.Obs.	12686
R2 Marg.	0.001
AIC	35301.8
BIC	35361.4
RMSE	0.72

A1.1.4 Study 2: Game need satisfaction and play behavior in PowerWash Simulator

Table A1.4. Study 2: Complete model summaries for game NS → play behavior

	Session Length	Time to Next Session
Intercept	4.218	2.414
	[4.202, 4.233]	[2.376, 2.451]
	s.e. = 0.008	s.e. = 0.019
	t = 530.451	t = 125.734
	p = <0.001	p = <0.001
Game need satisfaction (within)	0.009	-0.044
	[-0.003, 0.021]	[-0.082, -0.005]
	s.e. = 0.006	s.e. = 0.020
	t = 1.409	t = -2.235
	p = 0.159	p = 0.025
Game need satisfaction (between)	0.011	-0.009
	[0.003, 0.019]	[-0.035, 0.016]
	s.e. = 0.004	s.e. = 0.013
	t = 2.555	t = -0.722
	p = 0.011	p = 0.471
prev_session_length	0.001	
	[0.001, 0.001]	
	s.e. = 0.000	
	t = 14.287	
	p = <0.001	
prev_session_gap		0.000
		[0.000, 0.000]
		s.e. = 0.000
		t = 7.113
		p = <0.001
SD (Intercept pid)	0.234	0.701
SD (game_ns_cw pid)	0.028	0.159
Cor (Intercept game_ns_cw pid)	-0.441	0.118
SD (Observations)	0.649	1.896
Num.Obs.	22742	20724
R2 Marg.	0.010	0.003
R2 Cond.	0.124	0.125
AIC	242285.4	185815.0
BIC	242349.6	185878.5
ICC	0.1	0.1
RMSE	0.63	1.83

A1.2 Diagnostics

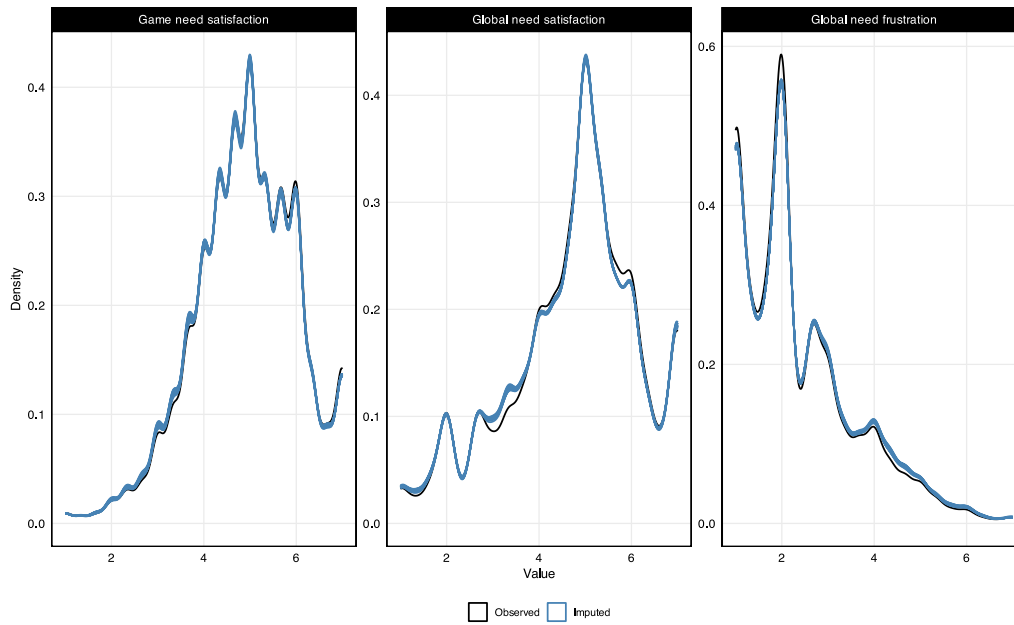


Figure A1.1. Imputed vs observed distributions for need satisfaction/frustration variables

A1.3 Sensitivity Analyses

We conducted several sensitivity analyses to assess the robustness of our findings regarding the relationship between need satisfaction/frustration and subsequent play behavior.

A1.3.1 S1: Temporal window robustness

Testing whether the temporal window affects results. The main analysis used 24 hours post-survey. Here we test: (a) 12 hours post-survey, (b) 6 hours post-survey, and (c) 24 hours pre-survey (reverse temporal ordering to test bidirectionality).

Table A1.5. S1: H2 associations across different temporal windows. Main analysis (24h post-survey) shown for comparison. Pre-survey window tests reverse temporal ordering.

Parameter	24h post	12h post	6h post	24h pre
Game need frustration	0.042 (0.277)	0.04 (0.235)	0.043 (0.19)	0.14 (<.001)
Global need frustration	-0.08 (0.062)	-0.016 (0.668)	-0.012 (0.751)	-0.081 (0.07)

A1.3.2 S2: Random effects specification robustness

Random slopes allow associations to vary across individuals, which is theoretically appropriate for these constructs. The main analysis used a random intercept only model due to convergence issues in frequentist estimation. Here we test whether this simplification affects fixed effect estimates by comparing four specifications: (a) no random slopes (main model), (b) random slope for game NS within-person only, (c) random slope for global NF within-person only, and (d) both random slopes simultaneously using Bayesian estimation (which handles complex random effects more robustly).

Table A1.6. S2: H2 fixed effect estimates across random effects specifications. Frequentist estimates (first three columns) show estimate (p-value). Bayesian estimates show estimate [95% credible interval].

Parameter	No slopes	RS: game NS	RS: global NF	Both slopes (Bayesian)
Game need satisfaction (within)	0.042 (0.277)	0.036 (0.362)	0.043 (0.266)	0.039 [-0.034, 0.111]
Global need frustration (within)	-0.08 (0.062)	-0.08 (0.063)	-0.079 (0.093)	-0.063 [-0.153, 0.028]

A1.3.3 S3: Play volume (continuous outcome)

Testing whether the predictors have a linear association with play volume in minutes, rather than binary play occurrence. Uses Gaussian family for continuous outcome.

Table A1.7. S3: H2 with continuous play volume (minutes) as the outcome, rather than binary play

Parameter	Estimate	SE	t	p
Game need frustration	2.756	1.625	1.696	0.09
Global need frustration	-1.776	1.840	-0.965	0.335

A1.3.4 S4: Complete cases only (no imputation)

Testing whether multiple imputation introduced bias. Main analysis used MICE with PMM; here we analyze only complete cases.

Table A1.8. S4: H2 with complete cases only (no imputation)

Parameter	Estimate	SE	z	p
Game need satisfaction (within)	0.042	0.038	1.096	0.273
Global need frustration (within)	-0.077	0.043	-1.797	0.072

A1.3.5 S5: Full sample imputation (preregistered approach)

Main analysis imputed analytical sample only (≥ 15 waves, $N = 555$) for statistical soundness. Preregistration specified imputing all participants. Here we implement that approach for comparison, though note that imputing 80%+ missing data for sparse participants is statistically questionable.

Table A1.9. S5: H2 model comparison between analytical sample (≥ 15 waves) and full sample (preregistered)

Parameter	Analytical (≥ 15 waves)	Full sample
Game need frustration	0.042 (0.277)	0.037 (0.302)
Global need frustration	-0.08 (0.062)	-0.087 (0.024)

A1.3.6 S6: Interaction between game NS and global NF

Testing whether the association of global need frustration with play depends on recent game need satisfaction (i.e., do satisfied players respond differently to global need frustration?).

Table A1.10. S6: H2 with game NS \times global NF interaction

Parameter	Estimate	SE	z	p
Game need frustration	0.042	0.038	1.081	0.28
Global need frustration	-0.076	0.043	-1.755	0.079
Time to next session	0.038	0.041	0.921	0.357

A1.3.7 S7: Non-linearity test with splines

Testing whether the relationships between predictors and play behavior are non-linear by fitting natural splines to the H2 predictors. We use complete cases only (no imputation) for computational simplicity.

Table A1.11. S7: Model comparison between linear and spline specifications

Model	AIC	BIC	LogLik	N	ΔAic
Linear	9726.2	9784.1	-4855.1	10317	0.000000
Spline (3 df)	9730.9	9817.8	-4853.4	10317	4.640006

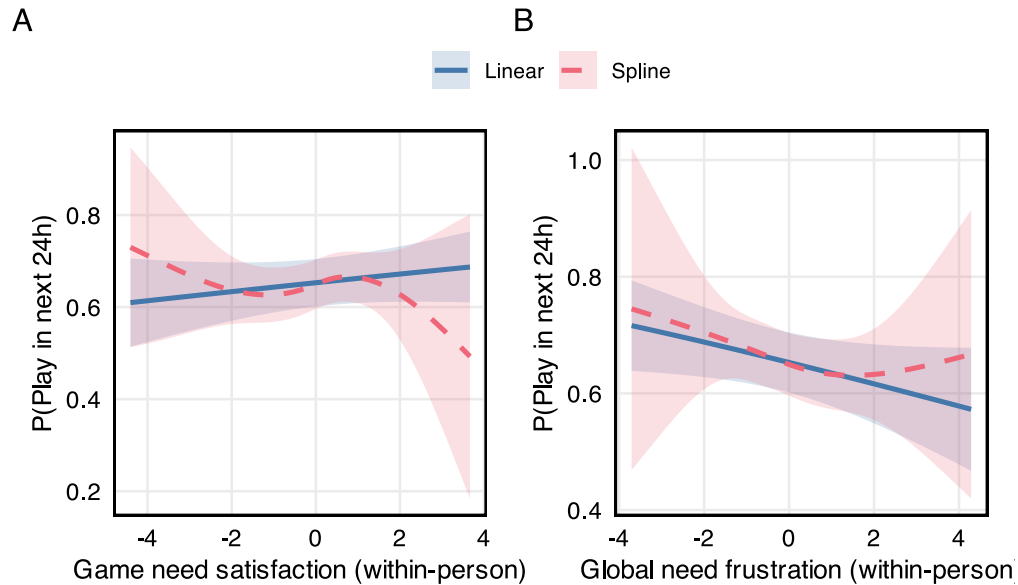


Figure A1.2. S7: Comparison of linear vs spline predictions for H2 predictors. Points show observed data (aggregated), solid lines show linear model predictions, dashed lines show spline model predictions with 95% confidence ribbons.

The spline model does not outperform the linear model ($\Delta\text{AIC} > 2$), suggesting that the relationships between need satisfaction/frustration and play behavior are adequately captured by linear terms.

A1.3.8 S8: Separate needs components

Testing whether associations with play differ across the three basic psychological needs (autonomy, competence, relatedness) rather than using composite need satisfaction scores. We test H2 separately for each need component.

Table A1.12. S8: Associations between need components and probability of subsequent play

Predictor	Estimate	SE	z	p
Game autonomy	-0.009	0.032	-0.290	0.772
Global autonomy frustration	-0.051	0.030	-1.734	0.083
Game competence	0.050	0.028	1.818	0.069
Global competence frustration	-0.068	0.028	-2.392	0.017
Game relatedness	0.021	0.023	0.934	0.35
Global relatedness frustration	0.005	0.034	0.160	0.873

All predictors are day-to-day fluctuations (i.e., within-person centered predictors). Outcome: Probability of playing in subsequent 24 hours.

A1.3.9 S9: Game need frustration and play behavior

Testing whether game need frustration (rather than satisfaction) is related to subsequent play behavior. This mirrors the H2a hypothesis but uses frustration instead of satisfaction.

Table A1.13. S9: Game need frustration predicting subsequent play

Parameter	Estimate	SE	z	p
Game need frustration	-0.07	0.035	-2.009	0.045

Results show that when people experience higher than usual in-game need frustration, they are less likely to play on the following day, but that this relationship is small. Nonetheless, in contrast to the robust null results for game need satisfaction across various specifications, this provides some initial evidence that need frustration may be more salient for day-to-day change in gaming behavior than need satisfaction.

A1.3.10 S10: H3 displacement by specific core life domain

The main H3 analysis aggregated all core life domains (work/school, social engagements, sleep/eating/fitness, caretaking) into a single binary indicator. Here we test whether specific domains show differential relationships with global need satisfaction.

Table A1.14. H3 sensitivity analysis: Effect of displacing specific core life domains on global need satisfaction

Domain	estimate	std.error	statistic	p.value
Work/School	-0.034	0.029	-1.199	0.23
Social Engagement	0.138	0.060	2.286	0.02
Sleep/Eating/Fitness	-0.087	0.024	-3.573	<.001
Caretaking	0.278	0.136	2.048	0.04

All models include random intercepts, random slopes, and AR(1) autocorrelation. Estimates represent the difference in global need satisfaction when the specific domain was displaced vs. not displaced.

Results showed that global need satisfaction was lower when gaming displaced work/school responsibilities and sleep/eating/fitness, but—contrary to expectations—tended to be higher when gaming displaced social engagements or caretaking.