

**Psychological Wellbeing, Sleep, and Video Gaming: Analyses of Comprehensive Digital
Traces**

[Stage 1 Programmatic Registered Report]

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Abstract

The increasing prevalence of video gaming has raised questions about its psychological effects, yet research has been hampered by challenges in accessing comprehensive behavioral and psychological data. We aim to address these gaps by collecting digital trace data across multiple gaming platforms and pairing it with intensive longitudinal psychological data. Using open-source software and collaborating with industry, we will track gameplay for 1,000 US emerging adults and 1,000 UK adults across Nintendo Switch, Xbox (US only), Steam, and iOS and Android for three months. Participants will complete 30 daily surveys (US sample) and six biweekly panel surveys (both regions) assessing subjective wellbeing, sleep quality, and need satisfaction. Three preregistered manuscripts, along with open code and data, will explore games' influence from three perspectives: basic psychological needs, sleep, and the structure of games. Study 1 will test relationships between in-game needs, needs in general, and subsequent play behavior, to assess whether gaming contributes to flourishing or compensation. Study 2 will examine the impact of late-night gaming on sleep quality, sleep duration, daytime sleepiness, and wellbeing exploring whether chronotype (natural inclination to be more active and alert in the morning, as opposed to evening) moderates these relationships. Study 3 will test the relation between multi-platform playtime and wellbeing, and its potential moderation by game genre. Together, these studies will inform associations between play and psychological wellbeing in rare detail by using more granular digital trace data.

Keywords: video games, digital trace data, sleep, basic psychological needs, game genre, health, wellbeing

Relationships Between Health and Logged Video Game Play Across Platforms

Upwards of half of adults and nearly all children in the UK and US regularly play video games (Entertainment Software Association, 2024; Ofcom, 2023), and the putative effects of this form of recreation on health are of interest to groups around the globe. A careful understanding of how play affects health can support games industry professionals interested in designing wellbeing-supportive games; policymakers seeking to regulate against potential downsides of games; clinicians managing patients whose gaming is severely impairing other areas of life; and parents and children looking to establish healthy boundaries around media use.

To date, however, research has had limited success in supporting these goals (Ballou, 2023). The lack of impact stems in large part from the challenges of accessing granular data about gaming behavior; of measuring mental health with sufficient detail to capture nuanced and short-lived effects; and of aligning theory and analysis approaches with growing evidence that effects of gaming and other media use relate primarily to the quality, rather than the quantity of use (Ballou, 2023; Büchi, 2024; Orben, 2022).

Today, researchers broadly agree that digital trace data—histories of user actions generated when interacting with technologies such as games—provides a valuable way to study behavioral engagement with games. Compared to self-report, digital trace data can provide much greater detail about what, when, and how much people play. Further, it alleviates concern about self-report biases—research consistently finds substantial discrepancies between digital trace data and participant recollections of use (Ernala et al., 2020; Kahn et al., 2014; Parry et al., 2021)—and high temporal fidelity, enabling studies using longitudinally intensive methods such as experience sampling approaches.

Fundamentally, accurate digital trace data of player behavior exists, because the gaming industry regularly collects player data at scale (El-Nasr et al., 2021). However, these

data are not in general accessible to independent researchers to study games' effects beyond industry motivations. In most cases, researchers must therefore build or rely on unstable technical systems to log data themselves or negotiate individual agreements with games companies who have historically been reluctant to share data. Where researchers have negotiated data access, this has typically included just one game or one platform—potentially just one small part of the person's gaming “diet” (Ofcom, 2023). People frequently play many games, across an average of 2.8 platforms for US and UK players (Ballou, Vuorre, et al., 2024)—for example, in the course of a week a person may play *Legends of Zelda: Tears of the Kingdom* on Nintendo Switch, *Balatro* and *Dredge* on Steam, and *Vampire Survivors* on iOS. To better understand the holistic effects of gaming, researchers therefore need to establish access to digital trace data across multiple platforms.

The second impediment to greater impact is the sparsity of mental health data. While digital trace data itself is often richly longitudinal, this has largely been paired with wellbeing surveys that consist of either a single wave (Ballou, Vuorre, et al., 2024; Johannes, Vuorre, et al., 2021) or three waves, each separated by multiple weeks (Larrieu et al., 2023; Vuorre et al., 2022). Early evidence suggests that effects of gaming, if present, may materialize and dissipate within 6 hours (Ballou, Vuorre, et al., 2024). Subjective wellbeing varies substantially over the course of a day in response to factors such as physical activity, internal states, social environments, and even contextual factors (Luhmann et al., 2021). Related research has found potentially meaningful relationships between smartphone use and wellbeing on the day level, which diminish to inconsequential within 3 days (Marciano et al., 2022). Experience sampling and daily diary methods, which have been embraced in social media research (Aalbers et al., 2021; Siebers et al., 2021) but have not yet been widely adopted in studies on gaming, give a greater chance of capturing nuanced, short-lived possible effects. Intensive longitudinal data can also help us to better differentiate within- and

between-person relationships and to investigate effect size variation (Johannes, Masur, et al., 2021).

Finally, evidence is increasingly clear that effects of gaming are nuanced and contextual, varying widely across people and within people over time based on what, how, why, where, and when play takes place. A collection of studies using digital trace data from companies such as Nintendo (Johannes, Vuorre, et al., 2021; Vuorre et al., 2022), Ubisoft (Larrieu et al., 2023), and Xbox (Ballou, Sewall, et al., 2024) more conclusively ruled out playtime as the primary determinant of mental health impacts, and supported long-standing calls to focus on quality and context of play (Ballou, Hakman, et al., 2024). Potential contextual factors are varied: For example, in-game social connections promote social capital (Depping et al., 2018), the time of day when play occurs relates to school performance (Drummond & Sauer, 2020), and certain predatory monetization schemes degrade user experience (Petrovskaya et al., 2022). To date, however, few of these qualitative aspects have been studied with digital trace data or intensive longitudinal mental health data, placing constraints on their generalizability.

Together, these limitations and trends point to clear next steps: collect comprehensive digital trace data (across multiple gaming platforms, as needed) so as to capture total play as accurately as possible; pair it with dense, longitudinal wellbeing data; and use this data for theory-driven investigations of play quality and context, rather than playtime.

Here, we aim to do that. We will collect two samples of players ($n = 1000$ US emerging adults, $n = 1000$ UK adults), collaborate with Nintendo and Microsoft to track their gameplay comprehensively across platforms (Nintendo Switch, Xbox [US only], Steam, and mobile). We will pair their gameplay data with 30-day daily surveys (US only) and 6 biweekly panel surveys measuring player psychological variables (e.g., subjective wellbeing, sleep quality, need satisfaction, and cognitive performance).

We will then analyze these data to understand how gaming relates to psychological outcomes from three perspectives: basic psychological needs (Study 1), sleep (Study 2), and game genres (Study 3). We describe each of these below.

Basic Psychological Needs in Games and Wellbeing (Study 1)

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 vital nutrients required for a person to live a fully functional life. 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).

Recent models have attempted to formalize certain SDT predictions in the games domain. One such model, the Basic Needs in Games (BANG) model of video game play and mental health (Ballou, 2024), builds upon the core SDT principle that any action's impact on mental health is mediated by basic psychological needs. By differentiating between playtime and quality of play, BANG helps explain previous seemingly conflicting findings that playtime itself is largely unrelated to mental health, but that some players do experience meaningful benefits or harms in relation to their video game play. By incorporating and

expanding upon SDT and the growing research on need frustration, BANG aims to account for both positive and negative potential impacts of gameplay, thereby explaining a greater portion of prior literature. To date, however, BANG remains largely untested. Hence, the goal of this study is to test several key BANG hypotheses. We label the predictions 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.

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 lives in general. Thus, BANG (B6) predicts:

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

Need satisfaction and frustration, across levels of generality, are proposed to have two key impacts. First, need satisfaction leads to wellbeing, while need frustration leads to illbeing. As this is firmly established in previous literature across life domains including games, we do not focus on this aspect here. Second, needs influence future behavior by virtue of updating expectations and by making opportunities to compensate for need deficits more salient.

Experiences of need satisfaction during a particular gaming session lead players to update expectations for future experiences with the current game, similar games, and gaming as a whole, such that greater need satisfaction leads to higher expectations for future need satisfaction. Under BANG (B8), need-related outcome expectations are conceptually similar

to intrinsic motivation, and the behavioral product of these expectations is therefore greater behavioral engagement.

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

SDT predicts that (global) need frustration results in compensatory behavior— people attempt to replenish needs that are not being met by altering their behavior. The dense need satisfaction offered by games constitute one way for people to compensate (Ballou et al., 2022). 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 an increased energy towards those activities. Given this, BANG (B9) predicts:

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

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 responsibilities (Drummond & Sauer, 2020), personal relationships (Domahidi et al., 2018), and physical health or sleep. Displacing activities in major life can reduce the ability to effectively engage in these areas, thereby reducing global need satisfaction. Thus, BANG (B5) predicts:

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

Late-Night Gaming, Sleep and Wellbeing (Study 2)

Concerns have been raised about the potential negative impacts of video gaming on sleep and overall wellbeing, particularly for adolescents and young adults and especially when gaming occurs late at night (Altintas et al., 2019; Exelmans & Van Den Bulck, 2015; Higuchi et al., 2005; King et al., 2013; Peracchia & Curcio, 2018). Late-night gaming has been shown to disrupt sleep patterns, reduce sleep duration, lower sleep quality, and increase daytime sleepiness (Exelmans & Van Den Bulck, 2015; Han et al., 2024; Kim, 2024; Kristensen et al., 2021). This is especially concerning given the far-reaching effects of sleep disturbances on cognitive and emotional functioning (Cain & Gradisar, 2010; LeBourgeois et al., 2017; McCoy & Strecker, 2011; Simon et al., 2020; Vriend et al., 2013). For instance, habitual gaming between 10 p.m. and 6 a.m. has been associated with an increased risk of depressive symptoms, partially mediated by daytime sleepiness (Lemola et al., 2011). Understanding the consequences of late-night gaming is thus vital for both gamers and health professionals.

Two key mechanisms have been proposed to explain the impact of late-night digital engagement—including gaming—on sleep. The first is the displacement hypothesis, which argues that late-night gaming is more harmful than daytime gaming because it cuts into sleep time (Twenge, 2019; Williams et al., 2008). Gamers often feel compelled to continue playing and struggle with self-regulation, which can lead to insufficient sleep (King & Delfabbro, 2009; Pirrone et al., 2024; Spada & Caselli, 2017). For example, adolescents experiencing a heightened sense of "flow" during challenging games delayed bedtime by up to 90 minutes (Smith et al., 2017).

The second mechanism involves arousal-related disturbances in sleep architecture caused by late-night gaming. Empirical studies have shown that extended gaming, especially when involving violent content, significantly decreases REM sleep and total sleep time (King

et al., 2013). Weaver et al. (2010) highlighted that increased arousal levels due to pre-sleep gaming extend sleep latency and alter the natural progression into sleep stages. This delay in sleep onset could be exacerbated by lower melatonin levels following an evening of gaming, compared to neutral activities like board games, which are crucial for regulating the sleep-wake cycle (Hartmann et al., 2019).

Negative effects of late-night gaming are often compounded among individuals with an eveningness chronotype—a group naturally predisposed to staying up late. Problematic gamers, who frequently possess this chronotype, are especially vulnerable to the detrimental effects of late-night gaming on sleep (Kristensen et al., 2021). Pre-sleep technology use may exacerbate the misalignment between their biological clock and societal demands by delaying sleep onset and reducing sleep duration, leading to poorer sleep quality and increased daytime sleepiness. Research has linked evening chronotype in adolescents to greater technology use at bedtime, in turn associated with delayed sleep onset, shorter sleep duration, and poorer sleep quality (Bruni et al., 2015; Gumport et al., 2021; Kortesoja et al., 2023; Reardon et al., 2023). Additionally, while Reardon et al. (2023) found that shorter sleep on weekdays was associated with greater psychological distress, technology medium and chronotype were not direct predictors of distress. Gumport et al. (2021) found that technology use improved emotional, social, cognitive, and physical health but worsened behavioral health, measured by the consumption of junk food, caffeine, alcohol, tobacco, and other substances, in evening-type adolescents. It remains unclear how strongly these findings apply to young adults and adults, as most research has focused on adolescent populations. This leaves an open question about the extent to which evening chronotypes in older age groups are similarly affected by pre-sleep technology use.

In sum, the literature indicates that video gaming, particularly when it occurs late at night, has significant implications for sleep quality, sleep duration, and overall wellbeing.

This disruption can be attributed to both the displacement hypothesis (Twenge, 2019; Williams et al., 2008) and arousal-related disturbances in sleep architecture (King et al., 2013). Individual differences, such as chronotype, may moderate these effects, with eveningness chronotypes particularly vulnerable to the negative consequences of late-night gaming (Kristensen et al., 2021). The present study aims to empirically test the following hypotheses regarding the relationship between late-night gaming and sleep outcomes:

H1: Late-night gaming is associated with poorer sleep quality (H1a), shorter sleep duration (H1b), higher daytime sleepiness (H1c), and lower wellbeing (H1d).

In addition to testing direct relationships between late-night gaming and various sleep-related outcomes are critical to understand, we further assess the potential moderating role of chronotype, which refers to a person's natural preference for activities during certain times of the day—morningness or eveningness. Individuals with an evening chronotype tend to stay up later and may be more inclined to engage in late-night gaming, potentially exacerbating the negative impacts on sleep and wellbeing. The combination of an evening chronotype and late-night gaming may even have a compounded effect on overall wellbeing, as both factors are independently associated with poorer mental health outcomes. Given this, we propose the following:

*H2: Chronotype moderates the relationships between late-night gaming and **all of the above outcomes**—sleep quality, sleep duration, daytime sleepiness, and wellbeing—such that these negative associations are stronger for individuals with more of an eveningness chronotype.*

By examining chronotype on a continuous scale as a moderating factor, this study seeks to provide a more nuanced understanding of the potential risks associated with late-night gaming and to identify individuals who may be most vulnerable to its negative effects.

Game Genres and Wellbeing (Study 3)

Video game effects research utilizing digital trace data often focuses on individual or a handful of games to understand the psychological processes and outcomes of digital play (Brühlmann et al., 2020; Johannes, Vuorre, et al., 2021; Larrieu et al., 2023; Vuorre et al., 2022). While understandable given the limited resources and lack of objective data available to independent researchers, it has left the field guessing whether identified relationships are unique to the studied titles or whether they apply universally across games. This limitation has restricted researchers' abilities to estimate the true prevalence of any found effects, leading to assumptions of generalizability and the formation of theories that fail to capture the diversity of the medium. Potential overgeneralization of findings has been well-documented in psychological research and is particularly pertinent to research on video games (Yarkoni, 2019).

With more than 10,000 new games released each year (Notis, 2021), an accessible classification system is essential for effectively studying and comparing video games and anticipating the effects of new releases. Genres, while imperfect as labels (Clarke et al., 2017), offer a pragmatic means of categorizing video games, providing utility for researchers, players, industry, and policymakers alike.

Studies have highlighted significant differences between video game genres in terms of their playtime and effects on player behavior, cognition, and wellbeing (André et al., 2024; Dobrowolski et al., 2015; Raith et al., 2021). Action games have been linked to increased visual attention (Palaus et al., 2017), cognitive and attentional control (Anguera et al., 2013; Bavelier & Green, 2019), and working memory (Blacker et al., 2014). Massively multiplayer online role-playing games (MMORPGs), first-person shooters, real-time strategy games (RTS), and Multiplayer Online Battle Arena (MOBA) games have been associated with higher gaming disorder (GD) symptoms (Rehbein et al., 2021). At the same time, randomized

controlled trials have employed genres like casual games and exergames to induce positive moods and reduce stress (Huang et al., 2017; Russoniello et al., 2009). These findings suggest that the effects of video games are not uniform and that genre plays a critical role in shaping gaming behavior and its impact on wellbeing.

It is important to recognize that genres are defined by convention and offer neither exclusive nor exhaustive categorisation—games might equally be categorized based on their business model, social features, content, and so on (Ballou, Hakman, et al., 2024). Psychologists have been trying to classify game genres for decades (Griffiths, 1993; Wolf, 2002), but must negotiate challenges in definition, overlaps between genres, and the continuous evolution of genres as new games are released. Thus, genres should not be viewed as definitive taxonomical statements about what games are but instead as crude but practical tools used to organize a growing library of varying video games, and an important first step in making the most of recent developments in digital trace data.

A recent systematic review highlighted the inconsistencies of genre classifications used in psychological research (Starosta et al., 2024). Of 96 examined articles, only 50 (52%) employed an existing genre classification, while 46 (48%) utilized a unique classification, of which 18 (19%) failed to specify the basis or definitions of their genre categorizations altogether. In most cases, genre classifications were either self-reported by participants or determined by the authors (Starosta et al., 2024). This subjectivity, where the same games are habitually classified into different genres, along with the emergence of new and hybrid genres, has put the validity of existing self-report or researcher-ascribed genre taxonomies into question.

The use of structured metadata repositories has been proposed as a more robust approach for conducting comparative research (Li & Zhang, 2020; Starosta et al., 2024). Structured metadata repositories, such as SteamDB, The Games Database, and the Internet

Gaming Database, involve both game developers and large samples of players in collaboratively crowdsourcing genre labels and tags. This approach accommodates the fluidity of genres and their evolution over time. Consequently, genres are increasingly understood not as fixed “kinds” or “species” but as processes that reflect how categories are created and evolve, offering insights into trends and understandings (Cohen, 1986). As video games continue to mature, and genres continue to be used by players, developers, and policymakers alike to inform decision-making, examination of the genre classification process becomes increasingly critical.

In sum, one portion of the literature has shown that playtime undifferentiated by genre is not a meaningful predictor of wellbeing, using data from both specific games (Larrieu et al., 2023) and platforms (Ballou, Sewall, et al., 2024; Ballou, Vuorre, et al., 2024). However, this has not yet been tested using comprehensive multi-platform play data. Thus, our first hypothesis predicts the absence of a meaningful relationship, this time with digital trace data across several platforms:

H1. Total cross-platform playtime is not meaningfully associated with fluctuations in general mental wellbeing over a 2-week period (H1a, "within-person") or with average wellbeing over the full study period (H1b, "between-person").

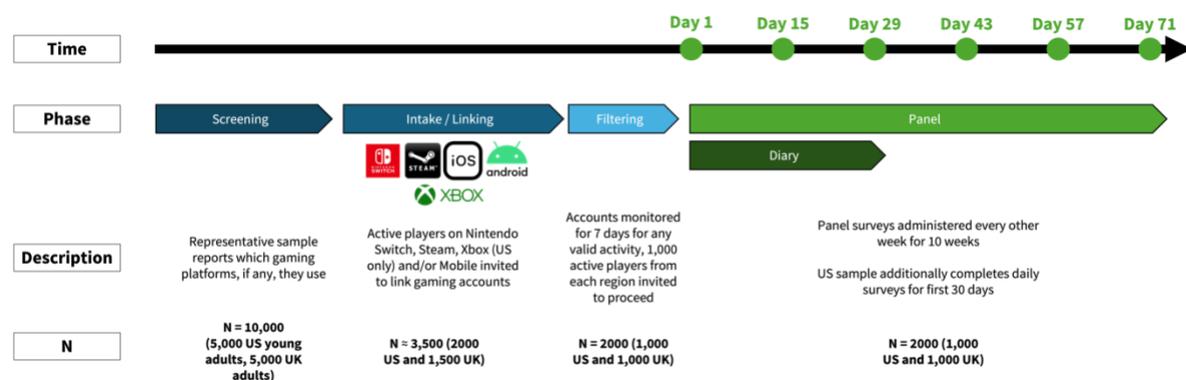
We will test this by fitting multilevel linear within-between model with total playtime as a predictor. Using the 90% confidence intervals of the within-person and between-person coefficients, we will conduct equivalence tests using an SESOI of .06 change in mean WEMWBS per 1-hour change in (daily) playtime associated with a .06 scale point change in mental health on a 1–5 scale, as previously used by Ballou, Sewall et al. (2024).

Consistent null findings for the effects of playtime on wellbeing have generated calls for the unpacking of raw decontextualized playtime into more informative measures that consider games’ varied characteristics and affordances (Ballou, Sewall, et al., 2024). Game

genres offer a structured way to differentiate between video games and their corresponding play experiences (Starosta et al., 2024). While genre differences are widely established (Azizi et al., 2018; Dobrowolski et al., 2015; Johnson et al., 2016; Rehbein et al., 2021), the effects of genre-level playtime on wellbeing are yet to be studied using digital trace data. Following previous literature, we predict that genres vary in their relation to wellbeing, with some potentially positive and others potentially negative, with varying strength. Put more formally:

H2. Genres differ in how playtime relates to fluctuations in general mental wellbeing over a 2-week period (H2a, “within-person”) and to average wellbeing over the full study period (H2b, “between-person”).

By fitting a model with playtime in each genre as a separate predictor, and using a joint Wald test to make inferences about the coefficients as a group as opposed to at an individual level (thus controlling the error rate; see Design Table 3), we will test whether one or more genres relate to wellbeing differently than the other genres, and thus whether it is justified to generalize video game effects across genres.



*Figure 1. Overview of the study design.
Green dots on the timeline represent panel survey waves.*

Method

Design

The study consists of four stages (Figure 1). In partnership with PureProfile as a sample-only panel provider, we will first screen a representative sample of UK adults aged 18–75 (N =

5000), and a representative sample of US emerging adults aged 18–30 (N = 5000) to determine what video game platforms different groups use. We apply different parameters to each region with the goal of focusing more heavily on emerging adults, a group subject to greater public health concern than adults (Odgers & Jensen, 2020). This focus on emerging adults is applied in the US rather than the UK because we have access to Xbox data in the US, allowing us to capture a larger proportion of total gameplay.

Those who (1) self-report playing video games, (2) self-report that at least 75% of their total video game play takes place on the platforms included in the study, and (3) are willing to link all relevant gaming accounts will be invited to complete an intake survey. Based on previous studies (Ballou, Sewall, et al., 2024; Ballou, Vuorre, et al., 2024), we estimate that approximately 2,000 US participants and 1,500 UK participants will be eligible to complete the intake survey.

In the intake survey, participants will link the gaming platforms they actively use (Table 1). For UK participants, this includes Nintendo Switch, Steam, Android and iOS. For US participants, this includes the same four alongside Xbox.

Using the linked accounts from the intake survey, we will collect baseline digital trace data for 7 days. This data will allow us to include only active players with valid gameplay data. Specifically, we will exclude participants who have no playtime logged on any self-reported platforms within that 7-day period. We will invite at most 1,000 participants from each region, randomly selected if needed, to proceed with the panel (US and UK) and diary (US only) surveys.

Eligible participants will then be invited to complete 6 waves of panel surveys, one every two weeks. Eligible US participants will additionally be invited to complete daily diary surveys for 30 days, concurrently with the first panel surveys. Running survey types

concurrently allows us to harmonize distribution across regions without delaying the UK sample on the US sample's account, and to minimize attrition.

Diary survey links will be sent every day at 7pm local time for the participant and remain available until 3am. Panel survey links will be sent every second week from the first day of the study at 7pm and remain available for 96 hours.

Ethics and Compensation

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).

Participants will be compensated for each survey they complete at a rate of approximately US\$10/hour, and will additionally be eligible for a lottery for a \$50 bonus payment if they complete more than 67% of administered surveys.

Platform	Source	Account Linking Process	Type of data collected	Privacy Notes
Nintendo Switch	Data-sharing agreements with Nintendo of America (US) and Nintendo of Europe (UK)	Participants share an identifier contained within a QR code on Nintendo web interface ¹ . Nintendo of America/Europe uses this identifier to retrieve gameplay data and share it with the research team.	Session records (what game was played, at what time, for how long) for 1 st party games (games published in whole or in part by Nintendo ² , but not by third party publishers such as Electronic Arts). In previous research, Nintendo-published games accounted for 65% of Switch playtime (Ballou, Vuorre, et al., 2024).	The numeric identifier contained in the QR code is dynamic and can only be linked to personal information by Nintendo of America/Europe.
Xbox (US only)	Data-sharing agreement with Microsoft	Participants consent to data sharing by opting in to the study on Xbox Insiders ³ with their Xbox account. Microsoft retrieves gameplay data for all consented accounts, and shares it with the research team in pseudonymized form.	Session records (what game was played, at what time, for how long). The name of the game will be replaced with a random persistent identifier for all third-party games (i.e., those not published by Xbox Game Studios ⁴). Genres for all de-identified game will be provided by Xbox.	When opting in to the study on Xbox Insiders, participants input a random numeric identifier given to them by the research team; this allows Microsoft to retrieve and share pseudonymous player data without the research team ever accessing participants' Xbox IDs or other account information.
Steam	Gameplay.Science	Participants sign up for Gameplay.Science (https://gameplay.science), an open-source platform for tracking Steam gameplay. Participants consent to have their gameplay data monitored for the duration of the study. Their Steam ID is authenticated using the official Steam authentication API (OpenID).	Incremental playtime per game (every hour, the total time spent playing during the previous hour)	Participants must make their gameplay details publicly available. Gameplay.Science has access to participants' Steam ID. Data is stored on encrypted servers to which only the research team has access. For details, see https://gameplay.science/privacy-policy .
iOS	iOS Screen Time Screenshots	At each panel survey, participants submit screenshots from the built-in iOS Screen Time app. These show details of the previous 2 weeks' of phone use (what app categories are used and for how long). Data is extracted using OCR.	Total weekly screentime by category (i.e., time spent on gaming apps, streaming apps, etc)	Screenshots may contain other potentially personal information such as device names. To mitigate this, we will extract only the relevant data from screenshots as they come in, and then delete the screenshots.
Android	ActivityWatch	Participants install the ActivityWatch app. At the end of the study, participants export and upload a JSON file containing their device usage for the study period.	Session records (what app was used, at what time, for how long)	ActivityWatch is open source, and stores data only on the local device. App developers cannot access usage data, nor is data transmitted to external servers. However, because ActivityWatch collects detailed device usage data beyond just gametime, we make donation of ActivityWatch data optional. We will remove any identifiers and store only pseudonymous session-level data (what apps were used at what time, for how long).

Table 1. Overview of platforms included in the study and the process of collecting gameplay data from these

¹ <https://accounts.nintendo.com/qrcode>

² https://nintendo.fandom.com/wiki/List_of_Nintendo_games

³ <https://support.xbox.com/en-US/help/account-profile/manage-account/guide-to-insider-program>

⁴ https://en.wikipedia.org/wiki/List_of_Xbox_Game_Studios_video_games

Measures

A full list of measures and constructs is available in the codebook within the Supplementary Materials (<https://github.com/digital-wellbeing/platform-study-rr>). The study includes several measures intended to maximize reuse value that are not used in the preregistered analyses (e.g., time use, caretaking responsibilities, player motivations, and personality) and so are not described here.

Screening

In the screening survey, participants will share demographic information (age, gender, employment status, educational attainment, and ethnicity), and report which video game platforms they are active players on.

Intake Measures

People who report being active on one or more of the gaming platforms in the study (Xbox, Nintendo, Steam, and mobile) will be invited to complete the intake survey. During the intake survey, participants will complete the account linking process for each platform to provide access to their gaming digital trace data. Participants will be asked to report their height and weight, educational attainment, and employment status, used to form indices of Body Mass Index (BMI) and socio-economic status.

Digital Trace Data

Digital Trace Data. Descriptions of each type of digital trace data from the 5 platforms (Nintendo, Xbox, Steam, iOS and Android) and how those data will be collected are described in Table 1.

Genre. Game genre for Nintendo, Steam, and Android will be obtained by cross-referencing game titles in the digital trace data with the Internet Games Database (igdb.com), which catalogues and categorizes games according to 19 distinct genres (e.g., Platformer,

Role-playing (RPG), Simulation). IGDB is, to our knowledge, the only database with complete metadata coverage of games across platforms that offers an API for programmatic data retrieval. The platform is crowd-sourced; community members can submit contributions (e.g., a new game or alternative categorization), which are vetted by admins and moderators before appearing in the database. The database is thus dynamic as some entries may change over time (although for popular games with many contributions this is rare); we will use the genres as they appear at the time of study completion. We will use the first and primary value of the “genres” field on IGDB as this is the most parsimonious categorization of games, and do not consider other variables such as “themes”. A complete list of genres on IGDB can be found in Appendix A.

For Xbox games whereby we do not have the final title names, we map genre labels provided by Xbox onto the IGDB taxonomy. Xbox uses a 17-genre scheme on the Xbox store, overlapping substantially 23-genre system used by IGDB (e.g., the “platformer” genre on Xbox is mapped onto the “platform” genre on IGDB). The mapping from Xbox is shown in Appendix B.

Panel Surveys

Wellbeing. To assess wellbeing, we will use The Warwick-Edinburgh Mental Wellbeing Scale (WEMWBS; Tennant et al., 2007), a standardized measurement tool designed to assess mental wellbeing in the general population. The WEMWBS consists of 14 positively worded statements, each reflecting aspects of mental wellbeing such as positive thinking, relaxation, and the ability to deal with problems. Respondents rate their experiences over the past two weeks on a 5-point Likert scale, ranging from "None of the time" to "All of the time." The scale is widely used in research and public health to monitor mental wellbeing, evaluate interventions, and inform policy decisions.

Chronotype. To assess chronotype, we will use the Munich Chronotype Questionnaire (MCTQ; Roenneberg et al., 2003), a widely recognized self-report instrument that captures an individual's natural sleep-wake patterns and circadian preferences. The MCTQ gathers detailed information about participants' sleep and wake times on both workdays and free days, enabling the calculation of various chronotype-related metrics. Among these, the Mid-Sleep on Free Days corrected for sleep debt (MSFsc) stands out as a key measure. MSFsc reflects the midpoint between sleep onset and wake time on free days—when individuals are free from work or social obligations—adjusted for the sleep debt accumulated during the workweek. This metric is a robust indicator of chronotype, with higher values signifying a preference for a later sleep phase (eveningness). MSFsc is particularly valuable for examining how chronotype moderates the relationship between late-night gaming and various sleep and wellbeing outcomes.

Sleep duration and quality. To measure sleep duration and quality, we will use the Pittsburgh Sleep Quality Index (PSQI; Buysse et al., 1989), a self-report questionnaire designed to assess various aspects of sleep quality and disturbances over the past month. The PSQI consists of 19 items, grouped into seven components, including sleep duration and overall sleep quality. These components are crucial for evaluating the effects of late-night gaming on both the quantity and perceived quality of sleep in the study.

Excessive daytime sleepiness. To measure daytime sleepiness, we will use the Epworth Sleepiness Scale (ESS; Johns, 1991), a validated tool that asks participants to rate their likelihood of falling asleep in various scenarios, such as sitting and reading, watching TV, or sitting in a car for an hour without a break. The ESS provides a score ranging from 0 to 24, with higher scores indicating greater levels of daytime sleepiness. This measure will be used to explore whether late-night gaming contributes to increased daytime sleepiness.

Diary Surveys

Need satisfaction and frustration (in-game). To measure satisfaction and frustration of basic needs at the situational level (game session), we will use single-item variants of BANGS autonomy, competence, and relatedness satisfaction subscales (6 items total). Single-item versions are needed to manage participant burden and can exhibit similarly high predictive validity as multi-item measures (Song et al., 2023), but there is currently no validated single-item need satisfaction in games measure. Thus, we selected highest-loading items for each subscale based on the original validation paper (Ballou, Denisova, et al., 2024) but caution that this has not been separately validated. For parsimony, we will calculate mean scores for satisfaction and frustration across all three needs.

Need satisfaction and frustration (general). To measure satisfaction of basic needs at the global level (life in general), we will use the single-item scales validated by Martela & Ryan (2024) (e.g., relatedness satisfaction “Today... I felt close and connected with other people who are important to me.”). As there are no validated single-item measures of global need frustration, we follow Martela & Ryan (2024)’s example and use the highest-loading items from the most well-established measure of need frustration, the Basic Psychological Need Satisfaction and frustration scale (Chen et al., 2015). We reworded the items to past tense to refer to the previous day. For simplicity, we will calculate mean scores for satisfaction and frustration across all three needs.

Sample Size Determination

We will collect the maximum sample size afforded by our resources, rather than one determined by a power analysis (Lakens, 2022): 1,000 UK participants for the panel surveys, and 1,000 US participants for the panel and daily diary surveys. We anticipate approximately 10% attrition per wave of the panel study, and 30% total attrition for the diary study.

We will leave each diary survey open for 8 hours, and each panel survey open for 96 hours, after which responses will not be included.

The minimum sample size required to proceed with our planned hypothesis tests is 50% response rate throughout the diary (total N after 30 days \geq 15,000) and panel (total N after 6 waves \geq 3,000) surveys. This ensures that we do not impute more data than we collect.

Hypothesis Testing Sensitivity

Due to a lack of prior data and results for the varied measures in the data, we conducted simulation analyses based on the anticipated size and structure of the data and one reasonable parameterization of the distribution of variables and the relations between them. We recognize that the sensitivity of our analyses will be determined by a wide range of interacting characteristics of the data (e.g., random slope SDs, autocorrelation coefficients, the true effect size, and so on) that would need to be simulated across a range of values, but doing so is a prohibitively difficult task given that it will not affect our sample size, which is fixed by resources.

These best-guess simulations found, for example, that the parameter estimating the relationship between a 1-scale point increase in gaming need satisfaction and general need satisfaction (Study 1 H1) had 95% CI .13 scale points wide. In Study 2 H1b, the 95% CI of the simulated estimate of a 1-hour change in daily late-night gaming predicting hours of sleep was .15 hours wide. In Study 3, the 95% CI of the simulated estimate of a 1-hour change in daily gaming on general mental wellbeing is .06 scale points wide. Together, these best-guess calculations suggest that our analyses will result in sufficient precision to separate small to medium relationships from noise.

Further details about the precision of our tests on simulated data are available in the Supplementary Materials.

Analysis Plan

For readability, the specific models are documented for each study in the design tables below, as well as in the Supplementary Materials (<https://digital-wellbeing.github.io/platform-study-rr/>).

The three planned outputs share an overarching modelling approach: each apply variations of multilevel models to account for the nested structure of the data. As and where necessary, these will (1) use person-level means and person mean-centering of time-varying variables to separate within-person and between-person relationships (Bell et al., 2019), (2) include AR(1) autocorrelation structure to account for the temporal relationship, and (3) use generalized multilevel models to account for discrete outcomes.

Analyses will be conducted in the latest stable version of R (R Core Team, 2024). Diary data models will be fitted with the *glmmTMB* package (Brooks et al., 2017); for ordinal scale measures in Study 2, we will employ the *ordinal* package (Christensen, 2023), while continuous panel measures will be analyzed using the *lme4* package (Bates et al., 2015). If we encounter convergence issues during estimation we will use Bayesian inference with the *brms* R package (Bürkner, 2021).

A working example of the analysis code on simulated data is available in the Supplementary Materials (<https://digital-wellbeing.github.io/platform-study-rr/>).

Exclusion Criteria and Missingness

We will exclude any telemetry rows wherein players have logged more than 16 hours of playtime across linked platforms in any single day; where a single session lasts longer than 8 hours; or where sessions have taken place in the future, indicating a technical problem or manipulation of the system clock for in-game benefits.

We will further include an attention check in the panel and diary surveys whereby participants are given a random duplicated item from the need satisfaction and frustration

measure. Responses where the two duplicate items differ by more than 1 scale point will be excluded.

After applying exclusions, missing data will be imputed using multiple imputation with the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011), assuming a mechanism of missing at random. Predictive mean matching will be applied to the data in wide format, with deviations to other imputation models considered only if this method proves inadequate. We will report the results for both the complete case and the imputed datasets.

We do not preregister any further exclusion criteria.

Data Quality Checks and Positive Controls

We will conduct various data quality checks, including (1) ensuring that wellbeing variables are correlated with each other at every wave, (2) ensuring that self-reported video game playtime is strongly positively correlated with digital trace playtime at every wave, and comparing the distribution of self-report data such as the WEMWBS to previous studies on similar populations.

We specify several positive controls (Table 2), which act as tests to ensure the data we collect is structured and co-related as expected. Passing these tests is therefore a prerequisite for proceeding with our analyses as planned.

Applicable Study	Test	Statistical Power
All studies	A significant positive correlation between self-reported video game play and digital trace playtime during the previous 2 weeks	Assuming $n = 9,300$ panel surveys (after 10% wave-on-wave attrition), a true population value of $r = .2$, an alpha of .05, and a one-sided test, power > 99%
All studies	There will be no overlapping sessions for a given individual on Nintendo or Xbox (we allow for possible overlap across different platforms, in case the user has two devices active simultaneously) AND there will be no cases where a player logs more than 60 minutes of playtime on Steam between adjacent hourly measurements	(N/A; fails if a single case occurs)
Study 1	Significant positive correlation between need satisfaction in general and daily life satisfaction	Assuming $n = 21,000$ diary surveys (after 30% total attrition), a true population value of $r = .2$, and an alpha of .05, power > 99%
Study 2	Significant positive correlation between social jetlag as calculated by the Munich Chronotype Questionnaire and daytime sleepiness.	Assuming $n = 4,440$ panel surveys with sleep measures (Waves 2, 4, 6 only + 10% wave-on-wave attrition), a true population value of Spearman's $\rho = .1$, an alpha of .05, and a one-sided test, power > 99%

Study 2	Significant negative correlation between sleep quality (Pittsburgh Sleep Quality Index sleep quality component) and Warwick-Edinburgh Mental Well-being Scale (WEMWBS).	Assuming $n = 4,440$ panel surveys with sleep measures (Waves 2, 4, 6 only + 10% wave-on-wave attrition), a true population value of Spearman's $\rho = -.1$, an alpha of .05, and a one-sided test, power > 99%
Study 3	Significantly higher playtime in shooter games for men as compared to women (Lange et al., 2021)	Assuming telemetry data for $n = 1,000$ (as attrition during surveys does not prevent us from collecting gameplay data), a true population difference of $d = .3$, and an alpha of .05, power > 99%

Table 2. Positive controls used to assess whether data is suitable for hypothesis tests, and estimated statistical power of these tests

Data and Code Availability

Simulated data, analysis code, and materials are available on GitHub (<https://github.com/digital-wellbeing/platform-study-rr>). Further documentation for the code is available on GitHub pages: <https://digital-wellbeing.github.io/platform-study-rr/>. At the time of Stage 2 submission, we will update these files with true data and archive a copy of the repository on the OSF.

Limitations

Across all studies, the absence of third-party Nintendo data means that we will be missing ~30% of playtime on that platform. Importantly, the distribution of genres among 3rd party games on Nintendo differs from the genres of 1st party games, and thus the relationships might differ for this missing 3rd party data. Across all platforms, idle time—periods when games are left running but not actively played—and account sharing could inflate playtime metrics, introducing bias. The playtime figures we report should be interpreted as an upper bound for the time spent actively playing on linked platforms during the study period. In all studies, our approach is observational and thus not positioned identify causal relationships between gaming and wellbeing.

In Study 1, reliance on self-reports of activities displaced by gaming introduces the risk of social desirability bias; participants might overstate intentions to engage in socially esteemed activities like exercising, which may not accurately represent their actual behavior in a counterfactual universe where they did not play games.

For Study 2, collecting sleep quality reports in the evening rather than in the morning may compromise data accuracy, as retrospective assessments can be less reliable than immediate reports upon waking.

Lastly, Study 3's lack of title information for 3rd party Xbox games means that we are reliant on Xbox's provided genre labels for categorizing games, whose criteria may differ or lag behind community-led labeling. While the options in Xbox's taxonomy largely correspond to the publicly available IGDB database, discrepancies may nonetheless influence our estimates of genre-specific playtime and wellbeing. We acknowledge that IGDB labels are themselves community-driven and prone to subjectivity, but elect to use these labels wherever possible (rather than relying exclusively on platform-provided genre labels) to maximize consistency across platforms, given that platform is likely to use a distinct set of opaque genre heuristics.

Study 1 Design Table

Research Question	Hypothesis	Sampling plan	Analysis Plan*	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
Does in-game need satisfaction contribute to overall need satisfaction?	H1. When individuals' in-game needs are better satisfied, they report greater global need satisfaction.	1,000 US adults, completing a diary study over 30 days.	Multilevel within-between linear regression whereby within-person centered game-level need satisfaction (gameNS_cw) predicts deviation from a person's typical global need satisfaction (globalNS). glmmTMB(globalNS ~ gameNS_cw + gameNS_cb + (1 + gameNS_cw pid) + ar1(day + 0 pid))	We did not conduct an a priori power analysis, as resource constraints dictated the maximum sample we could collect. The complexity of the data structure and lack of prior information about within-person playtime variance across days, effect size expectations, or meaningful smallest effect sizes of interests (SESOIs).	We will only interpret results subject to the data meeting the relevant positive controls specified: (1) a significant positive correlation between self-reported playtime and digital trace playtime, (2) no overlapping game sessions for a given individual on a particular platform, and (3) a significant positive correlation between global need satisfaction and life satisfaction. We will use statistical significance to determine whether the results support (p < .05) or fail to support (p > .05) the hypothesis. However, much greater emphasis will be placed on marginal outcomes, which we will contextualize in real-world terms so as to let readers make judgements about whether any statistically significant results are also practically significant.	H6 in BANG
Do positive play experiences result in more frequent future play behavior?	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	The hypotheses in Study 1 are better-suited to the diary study data, and therefore do not use the panel data (and by extension, the UK sample).	Multilevel logistic regression with the binary presence or absence of playtime in the subsequent 24 hours from survey completion as the outcome (playedLater), predicted by within-person centered in-game need satisfaction (gameNS_cw; H2a) and global need frustration (globalNF_cw; H2b). glmmTMB(playedLater ~ gameNS_cw + gameNS_cb + globalNF_cw + globalNF_cb + (1 + gameNS_cw + globalNF_cw pid) + ar1(day + 0 pid), family = binomial(link = "logit"))	Instead, we used simulated data to establish the approximate precision with which coefficients will eventually be estimated. In our assessment, these are sufficiently precise to be valuable and to differentiate statistical vs practical significance (see column right), but we leave further judgement to the reader.		H8 in BANG
Do players compensate for frustrated needs using games?	H2b. When individuals' global need frustration is higher, they are more likely to play video games in the 24-hour period after survey completion.		The telemetry data in study 1 consists of Xbox, Nintendo, and Steam.			Multilevel linear regression predicting global need satisfaction (globalNS) from the presence or absence of the player's most recent gaming session having displaced a core life domain (displacedCoreDomain). glmmTMB(globalNS ~ displacedCoreDomain + (1 + displacedCoreDomain pid) + ar1(day + 0 pid))
Is the displacement of core life domains more associated with harm than non-core domains?	H3. When a person's most recent gaming displaced a core life domain (work/school, social engagements, sleep/eating/fitness, or caretaking), their global need satisfaction will be lower					

*All multilevel models in Study 1 include random slopes and intercepts by participant (pid) for the predictor of interest, and an AR(1) autocorrelation structure for outcome measures. Between-person centered predictors (*_cb) are included for debiasing the within-person coefficient of interest, but are not used as part of the primary hypothesis test.

Study 2 Design Table

Research Question	Hypothesis	Sampling plan	Analysis Plan*	Rationale for deciding the sensitivity of the test	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
Does late-night gaming negatively impact sleep quality?	H1a: Late-night gaming is associated with poorer sleep quality.	The hypotheses will be tested using data from 1,000 US and 1,000 UK adults, who will complete six waves of panel surveys over 12 weeks. While the hypotheses could also be explored using the US diary data, the panel data is prioritized due to its broader geographic scope and larger	Multilevel ordinal regression whereby monthly average minutes of late-night play predicts sleep quality (PSQ), adjusting for covariates. clmm(psqi_6_ord ~ latenightPlaytime + {covariates} + (1 + latenightPlaytime pid) + (1 Gender))	(same as Study 1 Design Table)	(same as Study 1 Design Table, except positive control #3 is replaced by: (4) significant positive correlation between social jetlag and daytime sleepiness. and (5) significant negative correlation between sleep quality and wellbeing)	The sleep displacement hypothesis, which posits that late-night gaming displaces sleep time and thus negatively impacts sleep quality and leads to daytime sleepiness could be supported or challenged by the outcomes. If the hypothesis is confirmed, it would provide evidence that late-night gaming indeed displaces sleep, leading to poorer sleep quality, contributing to greater daytime sleepiness. Conversely, if the hypothesis is not supported, it could suggest that factors other than displacement, such as individual differences in sleep resilience or compensatory sleep behavior, play a more significant role in maintaining sleep quality and daytime alertness despite late-night gaming.
Does late-night gaming reduce total sleep duration?	H1b: Late-night gaming is associated with shorter sleep duration.		Multilevel linear regression whereby monthly average minutes played predicts total hours of sleep (PSQI), adjusting for covariates. lmer(total_hours_sleep ~ latenightPlaytime + {covariates} + (1 + latenightPlaytime pid) + (1 Gender))			
Does late-night gaming increase daytime sleepiness?	H1c: Late-night gaming is associated with higher daytime sleepiness.		Multilevel linear regression whereby monthly average minutes of late-night play predicts daytime sleepiness (epsTotal; Epworth Sleepiness Scale), adjusting for covariates. lmer(epsTotal ~ latenightPlaytime + {covariates} + (1 + latenightPlaytime pid) + (1 Gender))			
Does late-night gaming negatively impact wellbeing?	H1d: Late-night gaming is associated with lower wellbeing.		Multilevel linear regression whereby biweekly average minutes of late-night play (biweekly_latenightPlaytime) played predicts wellbeing (WEMWBS). lmer(wemwbs ~ biweekly_latenightPlaytime + {covariates} + (1 + biweekly_latenightPlaytime pid) + (1 Gender))			

<p>Does chronotype moderate the relationship between late-night gaming and sleep quality?</p>	<p>H2a/b/c/d: The negative association between late-night gaming and sleep and wellbeing measures is stronger for individuals with an evening chronotype (higher MSFsc).</p>	<p>sample size. Gaming data will include Nintendo Switch, Xbox, Steam, and Android (iOS data is not granular enough to calculate late-night play).</p>	<p>Multilevel regression models (ordinal or linear, depending on the outcome) testing the interaction between late-night gaming (monthly or biweekly average minutes played) and chronotype (MSFsc) on sleep quality, sleep duration, daytime sleepiness and wellbeing. Outcome ~ LateNightGaming * Chronotype + { Covariates } + (1 ParticipantID) + (1 Gender)</p>			<p>The findings could challenge or support theories of circadian misalignment and social jetlag, which suggest that evening chronotypes are more affected by late-night gaming due to misaligned sleep-wake patterns. Additionally, the results may inform the effectiveness of sleep hygiene guidelines that discourage late-night technology use. If the hypotheses are confirmed, it would suggest that evening-types are more vulnerable to these effects, reinforcing the need for tailored guidelines. Conversely, null results might imply that chronotype does not significantly moderate these relationships, or that evening-types have developed coping mechanisms.</p>
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* All multilevel models in Study 2 include random slopes and intercepts by participant (pid) for the predictor of interest, and a random intercept for gender. Covariates include age, BMI, SES index, region, and whether playtime falls on a weekend.

Study 3 Design Table

Question	Hypothesis	Sampling plan	Analysis Plan	Rationale for deciding the sensitivity of the test	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
How does time spent playing video games relate to wellbeing?	H1. Total cross-platform playtime is not meaningfully associated with fluctuations in general mental wellbeing over a 2-week period (H1a, "within-person") or with average wellbeing over the full study period (H1b, "between-person").	2,000 US and UK emerging adults, completing 6 bi-weekly panel surveys. Gaming data will include all 5 platforms for H1, and all but iOS for H2 (iOS weekly overviews do not include specific game titles from which to assess genre).	Multilevel within-between linear regression whereby playtime per genre (within- and between-centered) during the previous 2 weeks predicts wellbeing (WEMWBS), with a random intercept and random slopes for within-person centered playtime variables. Using the 90% confidence intervals of the within-person and between-person coefficients, we will conduct equivalence tests using an SESOI of .06 change in mean WEMWBS per 1-hour change in (daily) playtime. The .06 SESOI is based the minimally important difference for the WEMWBS (approximately .3-.4 scale points on a 1-5 scale), anchored to the amount of leisure time available to US adults, ~5 hours per day (Sturm & Cohen, 2019). A 5-hour change in playtime should predict at least a .3 scale point difference in wellbeing; effects smaller than this indicate that the average person does not have enough time to modulate play to an extent that it would meaningfully affect their wellbeing. The equivalence bounds are therefore $.3 / 5 = .06$ scale point change per hour of daily playtime.	(same as Study 1 Design Table)	We will only interpret results subject to the data adhering to the relevant positive controls: (1) a significant positive correlation between self-reported playtime and digital trace playtime, (2) no overlapping game sessions for a given individual on a particular platform, and (6) significantly higher shooter playtime in men compared to women. We will base our inferences for H1 on the lower (LB) and upper (UB) bounds of the 90% confidence interval around the predictor of interest as follows: <ul style="list-style-type: none"> • LB > [-.06] and UB < [.06]: absence of a practically significant association • LB > [-.06]: practically significant positive association • LB > 0 and UB > [.06]: positive association that may be practically significant • LB > 0 and UB < [.06]: positive association, but not practically significant • UB < [-.06]: practically significant negative association • LB < [-.06] and UB < 0: negative association that may be practically significant • LB > [-.06] and UB < 0: negative association, but not practically significant • Interval overlaps 0 and one or both equivalence bounds: inconclusive 	Practically significant relationships between total playtime and wellbeing would support the theory that raw quantity of video gaming is related mental health.
How does time spent playing particular genres of video games relate to wellbeing?	H2. Genres differ in how playtime relates to fluctuations in general mental wellbeing over a 2-week period (H2a, "within-		Model: Multilevel within-between linear regression whereby playtime per genre (within- and between-centered) during the previous 2 weeks predicts wellbeing (WEMWBS), with a random intercept and random slopes for within-person variables. Due to identifiability issues with the high number of coefficients, we will fix the correlation between random intercept and random slope to 0.		If the joint test is significant ($p < .05$), we will infer that there is at least one pair of genres whose relationships with within-person fluctuations in wellbeing (H2a) and/or with average wellbeing (H2b). To understand how genres vary in their relationship with wellbeing, we will use a caterpillar plot to visualize the estimates across all genres. We will NOT directly interpret differences between coefficients (e.g., saying that there is a significant difference	Significant variation between genres would support the theory that relationships between video game

	<p>person”) and to average wellbeing over the full study period (H2b, “between-person”).</p>	<p>Approach: We will conduct a joint Wald test on the coefficients in the above model. A joint test simultaneously assesses multiple related hypotheses, allowing us to determine whether the coefficient for any of the 23 genres differs from the others. The joint test uses the estimated coefficients and their covariance matrix to determine if a set of parameters jointly equals some specified value; this test follows the chi-squared distribution (Wald, 1943). The error rate is controlled in a similar manner as would be achieved by correcting the alpha level for all 23 surrogate hypotheses (García-Pérez, 2023).</p> <p>Test: We assess the probability of the data given the null that the genre coefficients as a group are equal vs the alternative that at least two coefficients are significantly different from each other. In R, this is specified as:</p> <pre>linearHypothesis(model, hypothesisMatrix = c(genre1 = genre2, genre2 = genre3, genre3 = genre4 genreN-1 = genreN)</pre>	<p>between genre A and genre B because one is statistically significant and one is not) without formal exploratory post hoc analyses, following e.g. Vuorre et al 2024), as the model entails a prohibitively high number of potential pairwise comparisons.</p>	<p>playtime and wellbeing are not generalizable across genres.</p>
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Appendix

Appendix A. List of IGDB genres. More information can be found <https://www.igdb.com/genres>

Genre
Pinball
Adventure
Indie
Arcade
Visual Novel
Card & Board Game
MOBA
Point-and-click
Fighting
Shooter
Music
Platform
Puzzle
Racing
Real Time Strategy (RTS)
Role-playing (RPG)
Simulator
Sport
Strategy
Turn-based strategy (TBS)
Tactical
Hack and slash/Beat 'em up
Quiz/Trivia

Appendix B. Mapping of Xbox-provided genre labels onto the IGDB genres

Microsoft-provided Genre Label	Corresponding IGDB Genre	Notes
Shooter	Shooter	
Role Playing	Role-playing (RPG)	
Action + Adventure	Adventure	
Puzzle + Trivia	Puzzle	
Sports	Sport	
Simulation	Simulator	
Racing + Flying	Racing	
Multi-Player Online Battle Arena	MOBA	
Other	-	“Other” games are rare, but have no mapping and will not be considered in the Study 3 genre analyses.

Platformer	Platform	
Fighting	Fighting	
Family + Kids		In almost all cases, games tagged family & kids on Xbox are also tagged with another genre—we will consider the secondary genre only and map to IGDB based on this.
Casino	Card & Board Game	
Strategy	Strategy	
Classics	Arcade	
Music	Music	
Card + Board	Card & Board Game	

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