Wellness Behavior On and Off Screen:

Affective Impacts of Engagement with Wellness Behavior and Media

Rebecca Sabrina Trockel

Master's Thesis: M.A. in Communication, Media Studies Track

Department of Communication, Stanford University

Advisor: Nilam Ram

June 2026

To the Directors of the Program in Communication:

I certify that I have read the thesis of Rebecca Sabrina Trockel in its final form for submission and have found it to be satisfactory for the degree of Master of Arts.

06/04/2026

Nilam Ram

Principal Advisor

Departments of Psychology and Communication

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Acknowledgements

This research would not have been possible without the continual guidance, encouragement, and support I received from my principal advisor, Nilam Ram, and Change Lab manager, A Garron Torres. The passion and care they bring to their work and their students are truly inspiring, and I am beyond grateful for the opportunity I had to be a part of the Change Lab during my time at Stanford.

After spending three years in the Change Lab, its mission, to “study change and attempt to invoke change,” continues to resonate deeply with me. Now, I can personally attest to the fact that the lab holds true to this mission, invoking change for the better not only at community-level scales, but also within each of the students who have the privilege of working there.

Beyond the technical skills I have gained as a part of the Change Lab, I have benefited from and am enormously grateful for the thoughtfulness, drive, creativity, collaboration, and kindness of each of the Change Lab members.

I would also like to thank all the professors and peers I have had the pleasure of learning from during my time at Stanford, who have provided me with an ideal environment to foster curiosity and growth.

Finally, I would like to thank my family and friends at Stanford and beyond for their unwavering love and confidence, which have both sustained me through challenges and allowed me to celebrate each success along this academic journey.

Abstract

The alarmingly high rates of mental health conditions and symptoms in the United States (Reinert, 2025), especially among individuals in disadvantaged groups (Marbin, 2022; Ridley et al., 2020; Patel et al., 2018; Pickett & Wilkinson, 2010), underscore the need to better understand the factors affecting mental health and identify effective interventions. Wellness behaviors, such as getting more sleep (Palmer, 2023; White et al., 2024), more physical activity (Mahindru, 2023; Larun et al., 2006; Peluso & Andrade, 2005), and avoiding harmful substances (Baum-Baicker, 1985; Geiger & MacKerron, 2016), are all associated with improved health and well-being. Although less is known about the impact of digital behaviors, they could be another accessible avenue for promoting well-being. This study fills this gap in research by leveraging (1) intensive longitudinal survey data collected fortnightly from adults over 52 weeks ($n = 60$; 31.7% male; $age_{mean} = 47$, range 18-78 years) and (2) passive screenome data collected through screenshots over the course of a year ($n = 5$) from the Human Screenome Project (Reeves et al, 2020) to conduct a mixed methods analysis of engagement with offline and digital wellness behaviors relationship to positive affect across socioeconomic groups.

Results showed no moderating effects of income across wellness behaviors ($p > .05$) and no significant associations between digital wellness engagement and positive affect ($p > .05$), leading to the key takeaway: wellness is truly an individual matter that may not be accurately captured by data. Detailed qualitative analyses of 5 participants support this point, revealing the broad range of contexts and intentions behind digital wellness engagement, which may shape its effects. Although more research and improved design are needed, digital wellness tools that account for users' broader life contexts and engagement intentions may still hold promise as low-cost, accessible ways to improve well-being.

Mental Health in the US: An Introduction

From main character depictions of mental illness in trending TV dramas (“Normal People”, Abrahamson & Macdonald, 2020; “Euphoria”, Levinson, 2019; “Queen Charlotte: A Bridgerton Story”, Rhimes, 2023), to Instagram life coaches’ 24-7 advice (Brooke, 2025), mental health has become a hot topic of pop culture conversation. Rates of mental health concerns, ranging from anxiety and depression to general psychological distress, have risen across the United States. Between 2009 and 2019, the depression rate in adolescents nearly doubled (8.1% to 15.8%) in the United States (Wilson, 2022), as did the rate of high-level anxiety in adults under 39 (9% to 21%; Adams, 2022). In 2019, one-fifth of young adults in the US had symptoms of depression and anxiety (Adams, 2022). These alarming rates worsened through the pandemic (Wilson, 2022), with the rate of adults reporting mental health symptoms reaching 63% for young adults (18–24) and 31% for the general population by June 2020 (Adams, 2022).

In a study of college students collecting data using the Generalized Anxiety Scale (GAD-7) at the initial stages of the pandemic in April 2020, all students, on average, met the threshold for moderate to severe anxiety (Hoyt et al., 2021). Thankfully, mental health concerns declined as the pandemic progressed. Halfway through the pandemic (June 2020), 63% of young adults (18–24) and 31% of all adults reported mental health symptoms (MHS: anxiety and/or depression (Adams, 2022). Just one month later, those rates declined again, with nearly half (48%) of young adults showing mental health symptoms severe enough to “warrant further screening or treatment” (Adams 2022).

An observational cohort study from April 2020 to March 22 for patients aged 12–25 found the same trend, with rates of anxiety and depression falling from 49 to 34% (Kinsella et al., 2023). Despite this decrease, demand for mental health resources remained high (Kinsella et al., 2023; Czeisler et al., 2021), with one in five young adults still screening positive for both anxiety and depression during the second year of COVID (Kinsella et al., 2023).

In the years following the pandemic (from 2021 to 2024), the prevalence of mental health symptoms among adults did not change significantly (Reinert, 2025). Still, in 2024, more than one in five adults in the United States reported experiencing some form of mental illness, totaling more than 60 million people (Reinert, 2025). Social stigma, healthcare costs, lack of access, and other barriers to treatment are key contributors to these startling numbers (Reinert, 2025; Czeisler et al., 2021). It is important to understand each of these barriers along with current trends affecting mental health in order to assess what could be done to improve the state of mental health in the US.

Access to Care Challenges

Recent data highlights the gravity and scale of unmet mental wellness needs. In 2019, a drastic 41% of young adults reported unmet need for mental health services (Adams, 2022). Data from June 2021 shows that of those with any mental health symptoms, over one-third (36%) reported unmet counseling needs (Adams, 2022). Between 2022 and 2023, one in four adults with mental illness reported an unmet need for treatment in the past year (Reinert et al., 2025). The most commonly cited reason for not seeking care was the belief that they should be able to handle their mental health on their own (70.5% in 2023), followed closely by the cost of treatment (59.8%; Reinert et al., 2025).

Financial barriers are, perhaps, the biggest obstacle. In 2023, 40% of individuals experiencing frequent mental distress could not afford to see a doctor. This problem is especially pronounced among those with Substance Use Disorder. Of these adults, over three-quarters (77.09%) did not receive the treatment they needed due to cost of care (Reinert, 2025). These barriers continue to widen the gap in mental health care for vulnerable populations (Singhal, 2024; Reinert, 2025). These persistent gaps in access to care point to a need for solutions that can expand the affordability and ease of mental health support.

Access to Care in a Digital World

While many barriers continue to restrict access to mental health care, new technology-based interventions offer hope. Crisis hotlines and digital tools like text-based counseling and app-based therapy have been designed to provide immediate, scalable assistance. The first telephone hotline in the U.S. was housed by the Children's Hospital of Los Angeles in 1968 (Roth, 2021), and the first suicide hotline was established in 1999, followed closely by the launch of The National Suicide Prevention Lifeline (NSPL) on January 1, 2005 (Roth, 2021). Over the following decade and a half, call volume steadily increased on the NSPL, reaching 2.2 million calls annually by 2018. In parallel, a steady increase in suicide rates, with over half a million suicide deaths between 2013 and 2023, sparked the creation of 988, an easy-to-remember number accessible by phone or text, aimed at simplifying and improving access to mental health crisis resources across the United States (Kaiser Family Foundation, 2025). These tools mark a step in the right direction, showing societal intention to provide more easily accessible mental health support.

Another significant step forward is the growth of Telehealth, defined as communication between providers and recipients of healthcare using technology like video conferencing, phone calls, or email (Cassity-Caywood, 2022). Before the COVID-19 pandemic, telemedicine faced several hurdles, including clinician public perception and regulatory limitations (Shaver, 2022). COVID-19 forced rapid adoption and growth of telehealth, with telemedicine appointments increasing by 766% in the first three months of the pandemic (Barney et al., 2020; Shaver, 2022).

Post-pandemic, telehealth remains a lasting component of healthcare delivery, helping improve access to care, especially for rural and stigmatized populations (Cassity-Caywood, 2022). Unfortunately, telehealth has also introduced a new disparity caused by access to and literacy with technology and has made it harder for clinicians to engage with patients (Barney et al., 2020; Cassity-Caywood, 2022). While the growth of digital tools marks a significant step toward expanding access to mental health care, it's clear that more research and continued efforts are needed to ensure these innovations reach and serve all populations effectively.

Income and Mental Health

In order to truly understand the current state of mental health, we must also consider how mental health affects different sociocultural groups in our nation. Patterns of mental health symptoms vary systematically by socioeconomic status (SES), highlighting stark disparities in emotional well-being.

Poverty is associated with higher rates of mental illness, with both mental illness increasing the risk of poverty, and poverty increasing the risk of mental illness (Marbin, 2022; Ridley et al., 2020; Patel et al., 2018; Pickett & Wilkinson, 2010). In 2024, adults with the lowest incomes, those earning less than 100% of the federal poverty level, or less than $15,060.00 (U.S. Department of Health and Human Services [HHS], 2024), reported the highest rates of both anxiety and depression symptoms, with 28% reporting symptoms of anxiety and 32% depression (Terlizzi & Zablotsky, 2024). The lowest income group also had the highest rate of severe cases of mental health concerns. In contrast, only 13.4% of adults in the highest income bracket (400% or more of the federal poverty level, or more than $60,240.00) reported symptoms of anxiety, and 15.4% reported symptoms of depression (Terlizzi, 2024; HHS, 2024). These disparities may be compounded, or even caused, by the problem that at-risk populations are often the least likely to receive the treatment they need (Pickett & Wilkinson, 2010; Reinert, 2025). In sum, there is a need for well-being improvement efforts that are accessible to low-income individuals (Patel et al., 2018; Terlizzi, 2024).

Offline Wellness Behaviors and Affect

Three behaviors that have been thoroughly researched and have consistently proven to play a key role in individuals' emotional well-being are physical activity, sleep, and alcohol consumption.

Regular engagement in physical activity, defined as a weekly allowance of "150 minutes" of modest to vigorous physical exercise (Mahindru, 2023), is linked to both higher positive affect and lower negative affect (Mahindru, 2023; Larun et al., 2006; Peluso & Andrade, 2005), with these benefits especially pronounced in women and individuals with low socioeconomic status (Saleh, 2023; Li et al., 2022; Begdache et al., 2022; Witters, 2026). Physical activity may serve as an accessible, low-cost, low-time-commitment tool for effective emotional regulation in at-risk populations (White et al., 2020; Mahindru, 2023).

Sleep duration and sleep quality are also strongly associated with well-being, with insufficient or poor-quality sleep predicting greater emotional instability and negative mood (Palmer, 2023; White et al., 2024). Children and adolescents are especially vulnerable to the negative mental and physical effects of sleep deprivation (Billings et al. 2021; Bruce et al. 2017; El-Sheikh et al. 2013). Humans need more sleep during these critical developmental windows, and a lack of it can derail brain maturation and impair prefrontal cortex functioning (Bruce et al. 2017; El-Sheikh et al. 2013). This is particularly concerning given that the peak and median age at onset for any mental disorder worldwide is 14.5 and 18 years, respectively. (Nagata, 2024) Notably, sleep disparities are evident across SES groups across age groups, with lower SES groups experiencing shorter and worse quality sleep, likely contributing to stark disparity in emotional well-being (Alcántara et al., 2017; Billings et al., 2021; El-Sheikh et al., 2013; Grandner et al., 2016; Whinnery et al., 2014).

Substance use, specifically alcohol use, shows momentary benefits in happiness when used in moderation, but these effects do not extend into long-term satisfaction (Baum-Baicker, 1985; Battista et al., 2010; Geiger & MacKerron, 2016). Heavy alcohol use is significantly associated with markers of low physical and emotional well-being, such as lower life satisfaction (Baum-Baicker, 1985), higher risk of anxiety and depression, and increased risk for premature death and disability (Geiger & MacKerron, 2016).

Digital Behaviors and Affect

Screentime Trends

An important behavior that has been given much less consideration is *screen time*, the amount of time people spend engaging with their digital devices (Cerit, 2025; Nagata, 2024). Currently, half of American teenagers spend over 4 hours per day on their phones, and screen time is increasing rapidly throughout the U.S. (Nagata, 2024). This rapid rise highlights the need to seriously consider the effects of screentime on well-being (Nagata, 2024). Although it's clear that digital engagement has become a defining feature of daily life, the relationship between screen use and emotional well-being remains uncertain. The findings of studies that have looked into the relationship between screen time and emotional well-being have been mixed (Brinberg et al., 2021). Some evidence associates higher screen time with depressive symptoms and poor affective states; however, the effect sizes thus far are generally small (Nagata, 2024). Many scholars note that these unclear findings are due, in part, to research methods including cross-sectional designs and imprecise measures of both media use and mental health (Cerit, 2025; Nagata, 2024). These mixed results could also be due to the heterogeneity in screen use. Research shows extreme between-person and within-person variability in how individuals engage with digital content (Brinberg, 2021), likely creating similarly extreme variability in the effects of that engagement. For some, technology may exacerbate stress, disrupt sleep, or fuel social comparison, while for others it could serve as a tool for connection, creativity, and self-improvement (Nagata, 2024; Brinberg, 2021; Nakshine, 2022). The fragmented findings have stalled the development of interventions and policy recommendations around digital behavior and well-being. Still, some research has attempted to explore potential links between digital engagement and mental health.

As mentioned above, adequate sleep is an established predictor of well-being. It makes sense, then, that sleep disruption and disturbance are heavily researched consequences of heavy phone use. Multiple studies have found that high mobile use is a risk factor for sleep disturbance (Sinha, 2022). A 2023 study by the American Academy of Sleep Medicine found that over three-fourths of Americans lose sleep due to digital distractions (2023). More than eight in 10 people (87%) keep their smartphone in the bedroom, often within arm's reach (American Academy of Sleep Medicine, 2023), and among adolescents, sleep loss resulting from nighttime screen use has been linked to depressive symptoms and suicidal ideation (Nakshine, 2022). Aside from sleep-related concerns, stress and anxiety also seem to rise with excessive screen engagement, potentially due to social comparison, constant notifications, and the physiological effects of blue light on the circadian rhythm (Nakshine, 2022).

Wellness App Use

Depending on the content, however, screentime may hold some promise for improving well-being. An increasing number of people are using their digital devices to engage with wellness apps (Tong, 2022). These platforms, ranging from mindfulness apps to fitness trackers to gratitude practice journals, may help promote positive affect (Lin, 2025; Tong, 2022; Walsh, 2019).

During the COVID-19 pandemic, a study found that using fitness apps and trackers was associated with higher engagement in physical activity (Tong, 2022). Based on this trend, using other wellness-oriented apps, such as sleep or diet, could also help promote those habits (Tong, 2022; Michie et al., 2013). Another category of wellness apps on the market is mindfulness and meditation-focused apps. Smartphone-based mindfulness training has been shown to produce immediate improvements in mood and stress, as well as long-term benefits like increased attention and emotional regulation (Howells et al., 2014; Walsh, 2019; Sedlmeier et al., 2012). Similarly, during the COVID-19 pandemic, digital gratitude practice was found to reduce stress, anxiety, tiredness, and loneliness (Brinberg et al., 2021; Cerit, 2025; Nagata, 2024). Interestingly, it also led users to feel less happy and optimistic overall (Lin, 2025). Overall, increasing evidence demonstrates that wellness apps may be successful in improving positive affect (Tong, 2022; Walsh, 2019).

These findings underscore that the relationship between screentime and well-being is still very much a gray area (Tong, 2022). To fully understand the relationship between screentime and wellness, we must analyze how people engage with their screens and how that engagement interacts with offline wellness behaviors.

Gaps in the Literature

The alarming rates and demographic disparities of mental health concerns and illness in the United States are a call to action to discover accessible and effective interventions. Wellness behaviors such as physical activity and sleep are known to correlate with improved health and well-being. Complementing these offline possibilities, growing evidence offers technology-mediated wellness as a new avenue for mental health improvement. However, more research is needed to understand how individuals interact with these digital tools and the impact of those interactions. Wellness apps could be especially meaningful for at-risk populations such as women and low-SES individuals, for whom these could offer low-cost, flexible, and scalable support for mental health and emotional well-being. Still, the current literature on screen time presents mixed and often contradictory findings. These inconsistencies highlight the need to increase the nuance of our study of screentime, differentiating screen use by content type, purpose, and individual intent. These distinctions could clarify when and for whom digital engagement supports or harms emotional well-being.

The Present Study

This study addresses this gap in the literature by examining both offline and online wellness behaviors, their associations with positive affect, and whether those associations are moderated by socioeconomic status. I first analyze sleep, physical activity, substance use, screen time, and wellness app use quantitatively, examining how these behaviors relate to individuals' positive affect and how these relationships vary by socioeconomic status. I then leverage smartphone screenome data to examine the details of participants' real-world use of wellness apps. This qualitative analysis of behaviors provides a detailed view of the patterns, context, and intention of individual digital wellness and other media use. Using this mixed-methods approach, this study develops a nuanced understanding of how online and offline wellness practices jointly shape emotional well-being. I specifically address the following research questions:

RQ1: What is the relationship between individuals' offline and online wellness behaviors and their positive affect?

RQ2: Does income moderate these relationships?

These findings are expected to have practical implications for future screenome analysis, individuals' daily media use, and the design of digital wellness tools as low-cost, accessible ways to promote well-being, particularly for vulnerable populations such as those with lower socioeconomic status.

Methods

The Human Screenome Project

This study used data from the Human Screenome Project (HSP, Reeves et al, 2020). Participants were recruited through the Qualtrics research panel and were required to reside in the United States, be the sole user of an Android phone, and provide informed consent. Participants completed fortnightly surveys for up to one year that included self-report measures of demographic variables, such as gender and household income, as well as a variety of health and behavioral topics, such as sleep, exercise, and affective states. In addition, Screenome smartphone data was collected via the Screenomics app, which took passive screenshots and recorded metadata such as app name and timestamp, every 5 seconds for the duration of the participant's enrollment in the study. This allows the calculation of quantitative phone usage data, such as mobile screen time and time spent on specific applications. Importantly, it also provides the opportunity to conduct qualitative analysis of participants' screen content and use. Participants were compensated $15 USD for each submission of fortnightly surveys, Screenome screenshots, and log data, earning up to $390. HSP adhered to national regulations and institutional policies and was approved by Stanford University's institutional review board, under protocol (IRB-56430). All data collected during the study was encrypted, transferred to, and stored on Stanford servers compliant with high-risk data and protected health information. Per the institutional protocols, no materials within this paper include identifiable participant information: quantitative modeling uses aggregated data, and qualitative vignettes use limited data with anonymous identifiers. Screenshot visuals were created by the research team as illustrative examples without any and were not taken from actual HSP data.

Data Preparation

Participants were first filtered to those 217 individuals who provided both fortnightly surveys and Screenome data, and excluded individuals flagged for professional survey taking or providing low-quality data. For the quantitative analysis, the sample was further filtered to the 60 participants who engaged with at least one mental health or wellness app during the year-long study period. For the qualitative analysis, I selected five participants (Table 2) who were high-wellness app users and exhibited differing correlation patterns between wellness app use and positive affect, including one woman in her late 20s, three women in their mid-30s, and one man in his mid-60s. High-wellness app users were identified by splitting the original pool of 60 participants into tertiles (high, medium, and low-wellness app usage groups) using the 33rd and 67th percentiles of total time spent on wellness apps. Selecting from these allowed me to explore how different quantitative relationships appear behaviorally in the screenome data (Table 2).

Participants

Table 1

Quantitative Analysis Participant Demographics

Participant Demographics

	N = 60[1]
Age	
18-24	6 (10%)
25-34	9 (15%)
35-44	11 (18%)
45-54	9 (15%)
55-64	15 (25%)
65+	10 (17%)
Gender	
Female	19 (32%)
Male	40 (67%)
Other	1 (1.7%)
Race	
White	41 (72%)
Native American	0 (0%)
Asian	2 (3.5%)
Black	7 (12%)
Pacific Islander	0 (0%)
Other	1 (1.8%)
Prefer not to answer	0 (0%)
Multiracial	6 (11%)
Missing	3
Hispanic/Latino Ethnicity	
Not Hispanic/Latino	47 (82%)
Hispanic/Latino	10 (18%)
Missing	3

[1] n (%)

Other Characteristics

	N = 60[1]
Income	
$14,999 or less	10 (17%)
$15,000 - $24,999	14 (23%)
$25,000 - $29,999	5 (8.3%)
$30,000 - $34,999	0 (0%)
$35,000 - $49,999	2 (3.3%)
$50,000 - $74,999	4 (6.7%)
$75,000 - $99,999	1 (1.7%)
$100,000 - $149,999	11 (18%)
$150,000 - $199,999	7 (12%)
$200,000 or more	3 (5.0%)
Don't know	3 (5.0%)

[1] n (%)

Table 2

Qualitative Vignette Case Study Participant Breakdown

Measure	Participant A	Participant B	Participant C	Participant D	Participant E
Age	Late 20s	Mid 30s	Early 20s	Mid 30s	Mid 60s
Gender	Female	Female	Female	Female	Male
Wellness Ratio & Pos Aff Correlation	0.49	-0.55	0.11	-0.01	0.27

Note: Participant demographic information was self-reported.

For the quantitative analysis, the 60 participants identified as 31.7% women, 66.7% men, and 1.7% another gender identity, with household income ranging from $14,999 or less to $200,000 or more, with clusters at the low end ($15k–$24,999, n=13) and mid-high end ($100k–$149,999, n=11; Table 1). For the qualitative analysis, the five participants included four females and one male, ranging in age from their late 20s to mid-60s. Although all participants were high wellness-app users, each exhibited a distinct relationship between wellness app use and positive affect. Participant A showed a moderate-to-strong positive correlation (r = 0.49), Participant B showed a strong negative correlation (r = -0.55), Participant C showed a weak positive correlation (r = 0.11), Participant D showed virtually no correlation (r = -0.01), and Participant E showed a modest positive correlation (r = 0.27).

Measures

Positive Affect

Positive affect, a component of individuals' emotional well-being, was measured each fortnight via self-reported responses to four items: happy, calm, satisfied, and relieved. Participants rated the extent to which they felt each emotion over the previous fortnight on a 0–100 numeric scale. A composite positive affect score (pos_aff) was calculated as the average of the four items, with higher values indicating greater positive affect (M = 62.05, SD = 24.05, median = 62.50, range = 0–100. The distribution was approximately normal with a slight negative skew ($skew$ = -0.48), indicating that participants tended to report moderately high positive affect overall (Table B1, Figure B1).

Screentime

Metrics for smartphone media use were derived from the screenshots and operating system metadata, specifically screentime and foreground application. All metrics were averaged daily within fortnightly periods, defined as the 14 days preceding each survey, except session duration, which was calculated as the average screen-on interval.

Screen time was measured as the daily average number of screenshots captured during screen-on periods. The data collection app captured screenshots every 5 seconds when the screen was on. These data were used to estimate total daily screen time in minutes per fortnight (screeentime_min), which was treated as a continuous numeric variable (M = 324.90, SD = 168.08, median = 298.59, range = 5.81 to 1022.94 minutes. The distribution was positively skewed ($skew$ = 0.81), indicating that while most participants clustered around moderate screen time levels, a smaller subset of participants reported substantially higher daily screen time use (Table B1, Figure B4). For analysis, Screentime was scaled in hours per fortnight by dividing by 60.

Wellness and Mental Health Applications

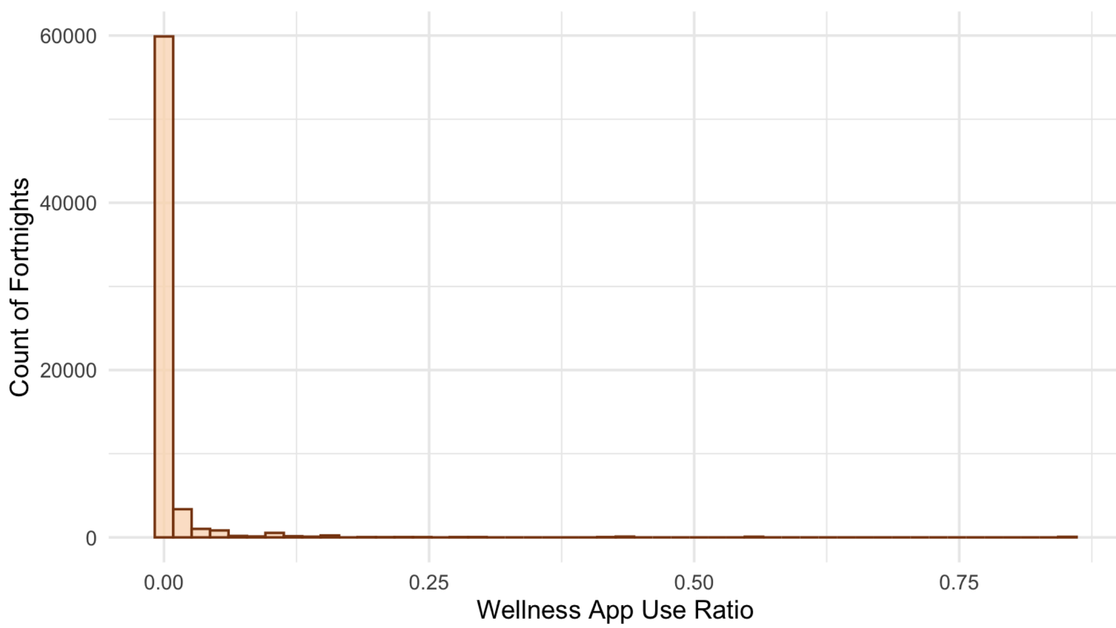
Mental health and wellness apps were identified through a multi-rater classification process conducted by members of the Change Lab at Stanford. First, all apps in the Screenome dataset were coded using a set of questions created by the Change Lab to create a research-appropriate categorization of the applications, including the binary screening question: “Is the purpose of this app to help users cultivate mental health and wellness?” (Appendix G). This screening question allows for the inclusion of both formal mental health applications (i.e., apps specifically designed for mental health support) and broader wellness applications (i.e., any apps intended to promote well-being).

Of the 7819 apps in the screenome, 282 were mental health and wellness-related apps (Appendix H). I manually categorized the type of wellness application as one of the following: fitness (48 apps), food and nutrition (12), games for relaxation or distraction (20), medical or physical well-being (55), music or audio (8), religion or spirituality (26), therapeutic apps (11), well-being and meditation (32), social (7), and other (63). To focus on wellness applications, apps categorized as "Social" and "Other" were excluded, resulting in a final analytic set of 212 wellness and mental health apps (Appendix H).

Wellness App Use Ratio

Figure 1

Proportion of Total App Time Spent on Wellness Apps



Note: Proportion of total app time spent on wellness apps is calculated per participant-fortnight. Wellness ratio was highly right-skewed, (M = 0.01, SD = 0.04, median = 0.00, range = 0–0.85, *skew* = 12.07) (Appendix B, Table B1, Figure B6)

Smartphone event log records were also used to calculate wellness app use time (Figure 1). To examine engagement with wellness apps, we considered wellness app use *relative* to overall app use. Using the variable of how much time each participant spent on an app in a given fortnight, I created a wellness app use ratio (wellness_ratio) variable, computed by dividing the time spent on wellness apps by total time spent on all apps during each fortnight. This ratio was multiplied by 100 for modeling, representing percentage-point changes in screen time. The majority of participants spent little to no time on wellness apps relative to their overall app use in a given fortnight, while a small subset of participants showed disproportionately high engagement (Figure 1).

Physical Activity

Physical activity was assessed each fortnight via self-report using the item: "Each time you exercised long enough to work up a sweat, how long did you exercise?" Responses ranged from 0 to 120 minutes per session, with higher values reflecting more time spent exercising (M = 23.12, SD = 23.60, median = 20.00, range = 0–120 minutes). The distribution was positively skewed (skew = 1.32), suggesting that most participants reported relatively low exercise duration, with a smaller subset reporting longer sessions (Table B1, Figure B2). For analysis, physical activity minutes were divided by 10 to reflect 10-minute increments.

Sleep Quality

Sleep quality (slp_quality) was measured each fortnight via self-report using an item that asked participants to rate their overall sleep quality over the past fortnight on a 0–100 numeric scale, with higher scores reflecting better *perceived* sleep quality (*M* = 66.98, *SD* = 22.20, median = 70.00, range = 0–100). The distribution was approximately normal with a slight negative skew (*skew* = -0.60), indicating that participants tended to report above-average sleep quality overall, with fewer participants reporting very poor sleep. The mean and median are close in value, further supporting the approximate normality of the distribution (Table B1, Figure B3). For analysis, sleep quality was divided by 10 to be on a 0 to 10 scale.

Alcohol

Alcohol consumption (alcohol) was measured each fortnight via self-report using an item asking participants to report the number of times they consumed alcohol during the previous fortnight. Responses ranged from 0 to 42 times per fortnight (*M* = 1.44, *SD* = 4.49, median = 0.00, range = 0–42 drinks; Appendix B). The distribution was highly positively skewed (*skew* = 4.29), with a median of zero indicating that the majority of participants reported no alcohol consumption in a given fortnight, while a small subset reported substantially higher consumption (Table B1, Figure B5).

Income

Income (income_mode) was defined as the modal response to fortnightly household income reports. Responses were recorded as categorical numeric variables with values 1: $14,999 or less, 2: $15,000 - $24,999, 3: $25,000 - $29,999, 4: $30,000 - $34,999, 5: $35,000 - $49,999, 6: $50,000 - $74,999, 7: $75,000 - $99,999, 8: $100,000 - $149,999, 9: $150,000 - $199,999, 10: $200,00 or more, 11: Don't know, 12: I prefer not to answer (M = 5.44, corresponding to approximately $35,000–$74,999, median = $50,000–$74,999, mode = $15,000–$24,999). Household income was treated as a numeric variable, and categorical responses 11: "don't know" and 12: "prefer not to answer" were dropped for modeling (Table 1).

Data Analysis

All data preparation, visualization, and quantitative analyses were conducted in R (version 4.x) using RStudio with tidyverse (Wickham et al., 2019), psych (Revelle, 2026), lme4 (Bates et al., 2015), lmerTest (Kuznetsova et al., 2017), ggplot2 (Wickham, 2016), corrplot (Wei & Simko, 2021), gtsummary (Sjoberg et al., 2021), entropy (Hausser & Strimmer, 2025), and effects (Fox & Weisberg, 2019). Linear multilevel models were used to account for repeated observations within individuals and examine within-person and between-person associations among selected variables and positive affect across income levels. Statistical significance was evaluated at $p < 0.05$.

Qualitative analysis of selected participants' digital behavior was conducted through viewing and coding participant screenshots. To do this, Structured Query Language (SQL) queries were executed in Google BigQuery to extract screenshot metadata for analysis. I used an image viewer developed by Change Lab members Yikun Chi and Charles Shi, adapted for vignette analysis in sequence by Manasi Garg, Destiny Tran Saucedo-Martinez, and me. Screenshots were reviewed for the selected subset of participants across targeted fortnights identified through longitudinal plots of affect and wellness app use. In total, I reviewed approximately 179,035 screenshots provided by 5 participants.

Quantitative Analysis

Before analysis, descriptive statistics (Appendix C), intraindividual variability metrics (Appendix D), and regression analyses (Appendix E) were used to obtain a foundational understanding of the study variables and to frame the study findings, as well as to conduct preliminary explorations of the data. Then, five multilevel models were fit using each predictor variable as the main predictor, income as a person-level predictor, and state positive affect as the outcome. The models use fortnight as a predictor to control for time-based trends over the study period. Random intercepts and slopes were included in all models to account for individual differences in both baseline positive affect and positive affect reactivity (Appendix F).

Equation (Level 1 Within-Person Model):

$$\text{Positive Affect}_{it} = \beta_{0i} + \beta_{1i}(\text{PredictorVariableState}_{it}) + \beta_{2i}(\text{Fortnight}_{it}) + e_{it}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{PredictorVariableTrait}_{i}) + \gamma_{02}(\text{Income}_{i}) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{PredictorVariableTrait}_{i}) + \gamma_{12}(\text{Income}_{i}) + u_{1i}$$

$$\beta_{2i} = \gamma_{2}$$

Qualitative Analysis: Vignettes

For selected individuals, a specific fortnight was identified for qualitative analysis using the longitudinal plots of positive affect, wellness app ratio, and total time spent on specific wellness apps, and selecting fortnights with notable patterns. Fortnights of interest were identified by outstanding peaks or dips in positive affect, in wellness app use, and in the use of notable mental-health and wellness apps. Screenshots from those fortnights were viewed and segments that included wellness-app use were qualitatively tagged in detail, creating a vignette of digital behavior

Results

The data descriptives showed no linear patterns in affect or wellness behaviors across income categories (Appendix D, Figure D1). However, regression analyses revealed that higher income was significantly associated with lower variability across all variables, with the strongest effect for positive affect ($R^2 = 7.68\%$; Appendix E), supporting the prediction that higher-income individuals have more stable affective states and behavioral patterns. An intraclass correlation coefficient (ICC) analysis revealed that 72% of the variation in positive affect was attributable to stable between-person differences, and 28% to within-person fluctuations over time, supporting the use of multilevel models. Multilevel modeling was used to examine the relationships between offline and online wellness behaviors and positive affect, and the moderation of these relationships by income (Table 3).

Table 3

Wellness Behaviors (Wellness app use, Physical Activity, Sleep Quality) and Positive Affect Across Income Categories Model Results

	Model 1: Wellness App Use		Model 2: Physical Activity		Model 3: Sleep Quality		Model 4: Alcohol Use		Model 5: Screen Time	
Predictor	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
Fixed Effects										
Var Name (Intercept)	**59.22****	2.90	**58.69****	2.765	**58.49****	2.10	**59.14****	2.91	**58.95****	2.97
Fortnight	**0.21****	0.01	**0.25****	0.01	**0.18****	0.01	**0.25****	0.01	**0.23****	0.01
Trait wellness behavior	−0.191	2.62	2.47	1.50	**7.77****	1.18	−0.12	0.82	−0.75	1.19
Income	1.002	1.05	0.96	1.00	1.17	0.76	0.82	1.09	0.86	1.11
State wellness behavior	−1392.00	920.40	**1.65****	0.46	**2.10****	0.40	**5.74***	2.34	−0.05	0.58
Trait behavior × Income	0.03	1.07	−0.34	0.52	−0.39	0.43	−0.31	0.47	0.08	0.42
Trait × State behavior	591.00	762.80	−0.04	0.26	−0.04	0.22	−0.71	0.56	−0.24	0.24
State behavior × Income	256.80	349.10	−0.02	0.17	−0.03	0.14	−0.49	0.86	−0.16	0.21
Trait × State behavior × Income	−88.47	317.70	0.09	0.09	0.09	0.08	0.18	0.32	−0.03	0.09
Random Effects										
Intercept variance (σ^2)		470.60		432.25		248.18		462.70		464.75
State wellness behavior Slope variance		37,290,000		11.34		8.71		194.80		17.14
Intercept–Slope correlation		0.19		−0.17		−0.13		−0.33		0.03
Residual		170.30		166.19		155.56		172.00		169.60

Note. N = 57 persons; n ≈ 61,739 observations nested within persons. Est. = unstandardized estimate. SE = standard error. Between-person components reflect person-mean-centered (trait-level) predictors; within-person components reflect deviations from individual means. All models include a random intercept and random slope for the within-person predictor. * $p < 0.05$. ** $p < 0.001$.

Model A. Affective Response to Wellness App Use Across Income

I fit a multilevel model with a random slope and random intercept, wellness app use (wellness_ratio) as the main predictor, income as another person-level predictor, and state positive affect as the outcome (Table 3)

Equation

(Level 1 Within-Person Model):

$$\text{Positive Affect}_{i□} = \beta_{0i} + \beta_{1i}(\text{WellnessState}_{i□}) + \beta_{2i}(\text{Fortnight}_{i□}) + e_{i□}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{TraitWellness}_i) + \gamma_{02}(\text{Income}_i) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{TraitWellness}_i) + \gamma_{12}(\text{Income}_i) + u_{1i}$$

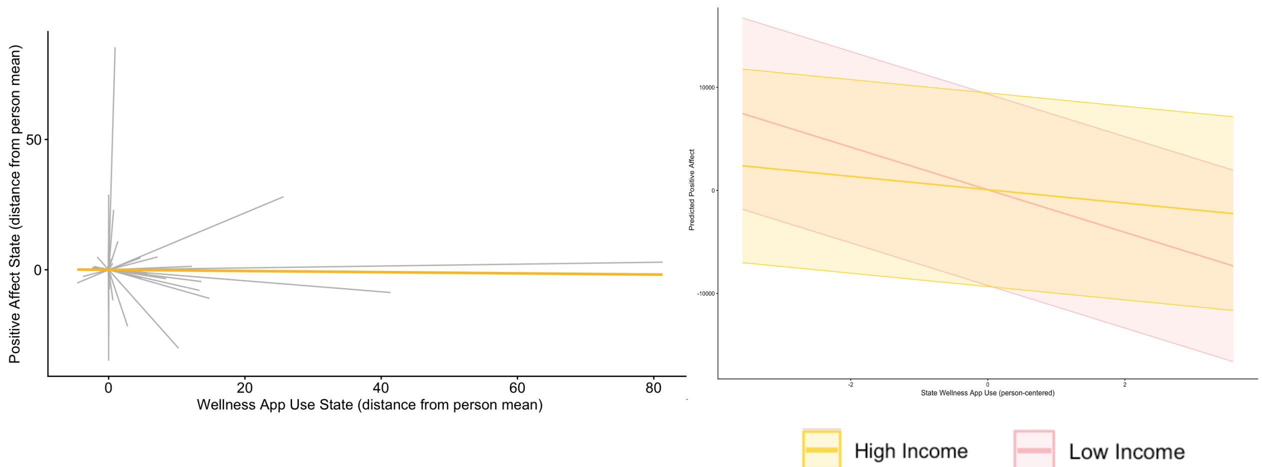
$$\beta_{2i} = \gamma_{20}$$

Neither how much individuals typically used wellness apps relative to others nor whether they used them more than their personal usual was significantly related to their fortnightly positive affect ($p_{\text{TraitWellness}} = .95$; $p_{\text{StateWellness}} = 0.19$). There was also no evidence that income moderated the relationship between wellness app use and positive affect, whether between-person ($p = 0.98$), within-person ($p = 0.47$), or in combination ($p = 0.79$) (Table 3).

The results are visualized in Figure 2. The overall trend (gold line) has a negative slope, consistent with the random-intercept model, which suggests that higher-than-usual wellness app use is associated with slightly lower positive affect. Although the plot shows that the line for low-income individuals (pink) has a steeper slope than the line for high-income individuals (gold), the income × within-person wellness app use interaction in the model was not significant (b = 256.8, p = .474).

Figure 2

a) Within-Person Association of Wellness App Use and Positive Affect and b) Within-Person Reactivity of Positive Affect to Wellness App Use Across Trait Income



Note. a) Each gray line represents an individual's within-person association between wellness app use and positive affect. b) The slope of the lines in this plot represents the degree of within-person positive affect reactivity to fluctuations in wellness app use.

Model B. Affective Response to Physical Activity Across Income

I fit a multilevel model with a random slope and random intercept, physical activity (pa_minutes) as the main predictor, income as another person-level predictor, and state positive affect as the outcome (Table 3).

Equation

(Level 1 Within-Person Model):

$$\text{Positive Affect}_{i\square} = \beta_{0i} + \beta_{1i}(\text{PhysicalActivityState}_{i\square}) + \beta_{2i}(\text{Fortnight}_{i\square}) + e_{i\square}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{TraitPhysicalActivity}_{i}) + \gamma_{02}(\text{Income}_{i}) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{TraitPhysicalActivity}_{i}) + \gamma_{12}(\text{Income}_{i}) + u_{1i}$$

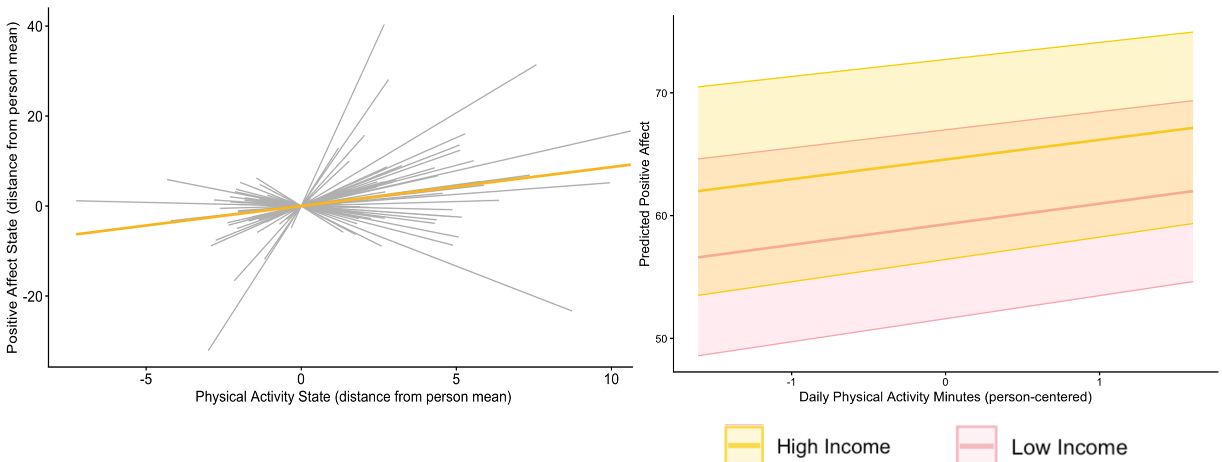
$$\beta_{2i} = \gamma_{20}$$

How much individuals typically engaged in physical activity relative to others had no significant impact on positive affect ($p = 0.11$). However, on fortnights where individuals were more active than their personal usual, they experienced a 1.6-point increase in positive affect ($p < 0.001$). Income had no effect on the relationship between physical activity and positive affect, whether between-person ($p = 0.52$), within-person ($p = 0.94$), or in combination (Table 3).

The results are visualized in Figure 3. The overall trend (gold line) has a positive slope, consistent with the model, suggesting that higher-than-usual physical activity is associated with higher positive affect. The plot shows that the lines for low- (pink) and high-income (gold) individuals are nearly parallel, with substantially overlapping confidence ribbons, suggesting that income does not moderate the relationship between physical activity and positive affect. This is consistent with the insignificant income × within-person physical activity interaction term in the model (b = −0.013, p = .936)

Figure 3

a) Within-Person Association of Physical Activity and Positive Affect b) Within-Person Reactivity of Positive Affect to Physical Activity Across Trait Income



Note. a) Each gray line represents an individual's within-person association between physical activity and positive affect. b) The slope of the lines in this plot represents the degree of within-person positive affect reactivity to fluctuations in physical activity.

Model C. Affective Response to Sleep Quality Across Income

I fit a multilevel model with a random slope and random intercept, sleep quality (slp_quality) as the main predictor, income as another person-level predictor, and state positive affect as the outcome (Table 3).

Equation

(Level 1 Within-Person Model):

$$\text{Positive Affect}_{i\square} = \beta_{0i} + \beta_{1i}(\text{SleepQualityState}_{i\square}) + \beta_{2i}(\text{Fortnight}_{i\square}) + e_{i\square}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{TraitSleepQuality}_{i}) + \gamma_{02}(\text{Income}_{i}) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{TraitSleepQuality}_{i}) + \gamma_{12}(\text{Income}_{i}) + u_{1i}$$

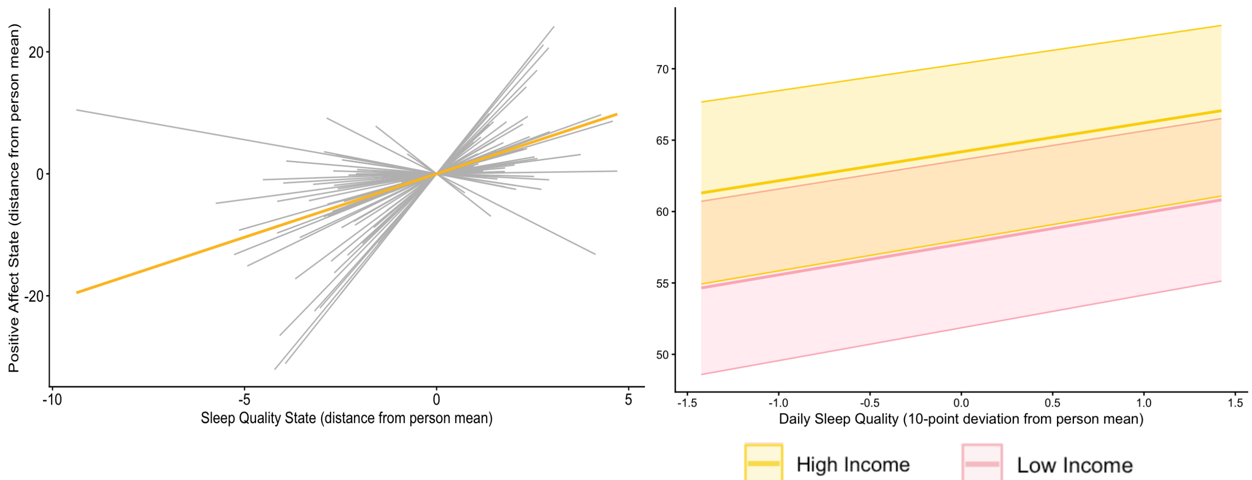
$$\beta_{2i} = \gamma_{20}$$

Both how well individuals sleep relative to others and whether they slept better than their personal usual had a significant impact on positive affect ($p < 0.001$). Individuals who typically reported better sleep quality experienced a 7.77-point increase in positive affect for every 10-point increase in average sleep quality, and on fortnights where individuals slept better than their personal usual, they experienced a 2.10-point increase in positive affect. Income had no effect on the relationship between sleep quality and positive affect, whether between-person ($p = 0.37$), within-person ($p = 0.86$), or in combination ($p = 0.30$; Table 3).

The results are visualized in Figure 4. The overall trend (gold line) in panel A has a positive slope, consistent with the random-slope model, suggesting that better-than-usual sleep quality is associated with higher positive affect. The plot shows that the lines for low- (pink) and high-income (gold) individuals are nearly parallel, with substantially overlapping confidence ribbons, suggesting that income does not moderate the relationship between sleep quality and positive affect. This is consistent with the insignificant income × within-person sleep quality interaction term in the model ($b = -0.026$, $p = .858$).

Figure 4

a) Within-Person Association of Sleep Quality and Positive Affect b) Within-Person Reactivity of Positive Affect to Sleep Quality Across Trait Income



Note. a) Each gray line represents an individual's within-person association between sleep quality and positive affect. b) The slope of the lines in this plot represents the degree of within-person reactivity of positive affect to fluctuations in sleep quality.

Model D. Affective Response to Alcohol Use Across Income

I fit a multilevel model with a random slope and random intercept, alcohol use (alcohol) as the main predictor, income as another person-level predictor, and state positive affect as the outcome (Table 3).

Equation

(Level 1 Within-Person Model):

$$\text{Positive Affect}_{i\square} = \beta_{0i} + \beta_{1i}(\text{AlcoholState}_{i\square}) + \beta_{2i}(\text{Fortnight}_{i\square}) + e_{i\square}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{TraitAlcohol}_{i}) + \gamma_{02}(\text{Income}_{i}) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{TraitAlcohol}_{i}) + \gamma_{12}(\text{Income}_{i}) + u_{1i}$$

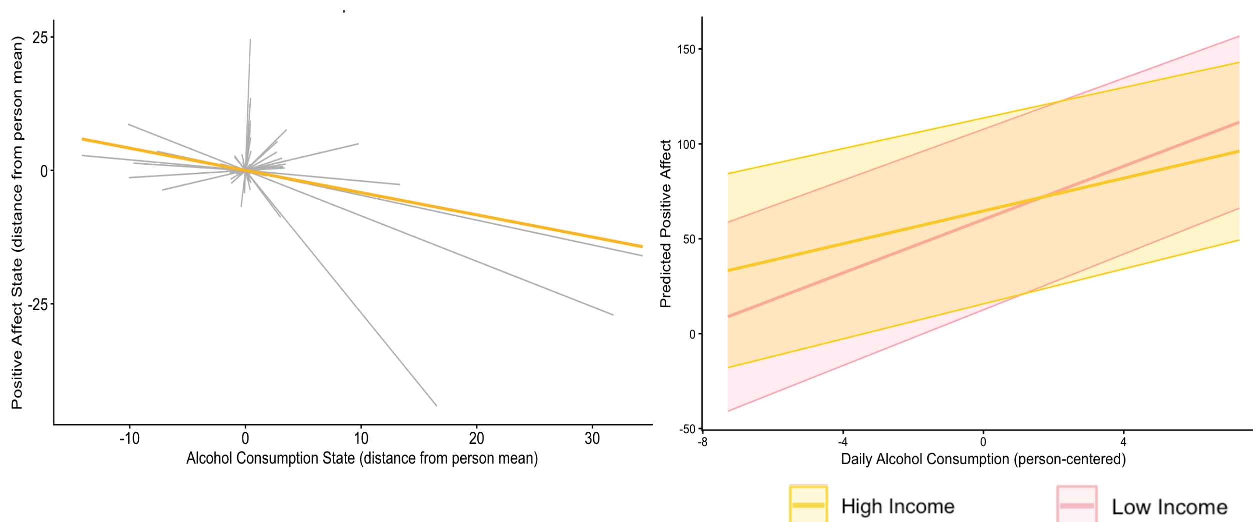
$$\beta_{2i} = \gamma_{20}$$

How much individuals typically drank relative to others did not significantly affect positive affect ($p = 0.89$). However, on fortnights where individuals drank more than their personal usual, they experienced a 5.74-point increase in positive affect ($p = 0.02$). Income had no effect on the relationship between drinking and positive affect, whether between-person ($p = 0.52$), within-person ($p = 0.57$), or in combination ($p = 0.58$; Table 3).

The results are visualized in Figure 5. The golden line in panel A represents the average within-person effect. The gold line slopes downward and does not reflect the (significant) predicted results in the multilevel model ($b = +5.744$, $p = .020$). It may correspond to the raw bivariate slope of between-person differences, suggesting that individuals who drink more than usual tend to report lower positive affect. The plot shows that the lines for low (pink) and high (gold) income individuals overlap with similar slopes and substantially overlapping confidence ribbons, suggesting that income does not meaningfully moderate the relationship between alcohol consumption and positive affect. This is consistent with the non-significant income × within-person alcohol use interaction in the random-slope model ($b = -0.491$, $p = .572$).

Figure 5

a) Within-Person Association of Alcohol Consumption and Positive Affect b) Within-Person Reactivity of Positive Affect to Alcohol Consumption Across Trait Income



Note. a) Each gray line represents an individual's within-person association between alcohol use and positive affect. b) The slope of the lines in this plot represents the degree of within-person positive affect reactivity to fluctuations in alcohol consumption.

Model E. Affective Response to Screen Time across Income

I fit a multilevel model with a random slope and random intercept, screen time (screentime_min) as the main predictor, income as another person-level predictor, and state positive affect as the outcome (Table 3).

Equation

(Level 1 Within-Person Model):

$$\text{Positive Affect}_{i\square} = \beta_{0i} + \beta_{1i}(\text{ScreentimeState}_{i\square}) + \beta_{2i}(\text{Fortnight}_{i\square}) + e_{i\square}$$

Where (Level 2 Between-Person Model):

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{TraitScreentime}_i) + \gamma_{02}(\text{Income}_i) + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{TraitScreentime}_i) + \gamma_{12}(\text{Income}_i) + u_{1i}$$

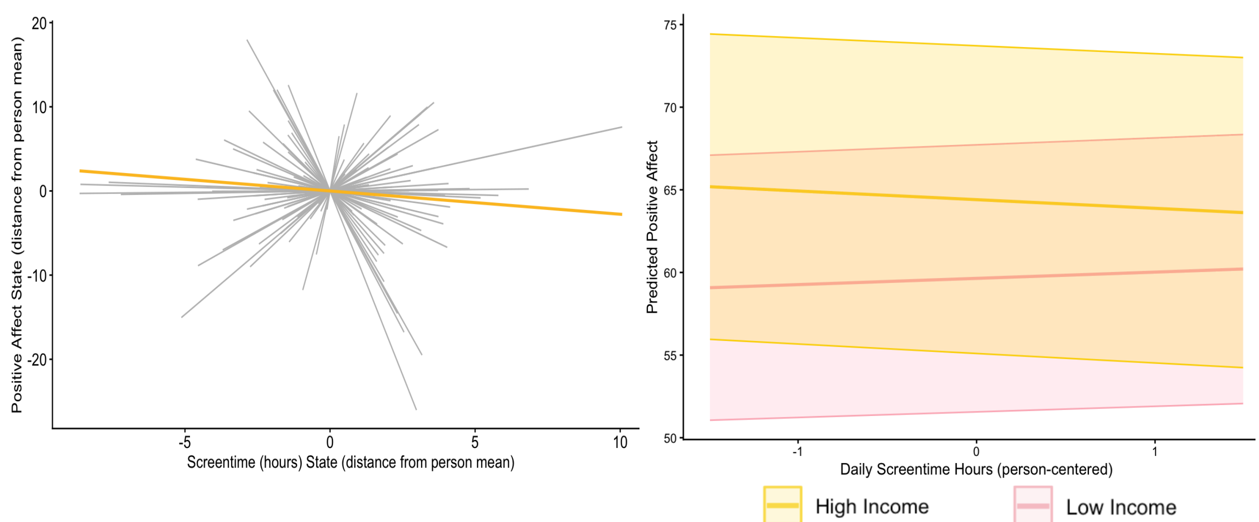
$$\beta_{2i} = \gamma_{20}$$

Neither how much time individuals typically spent on screens relative to others nor whether they used screens more than their personal usual had a significant impact on positive affect ($p_{screentime\_trait} = 0.53$, $p_{screentime\_state} = 0.93$). Income had no effect on the relationship between screen time and positive affect, whether between-person ($p = 0.85$), within-person ($p = 0.45$), or in combination ($p = 0.75$; Table 3).

The results are visualized in Figure 6. In panel A, the overall trend (gold line) has a slight negative slope, consistent with the multilevel model, which also finds a negative (non-significant) relationship ($b = -0.050$, $p = 0.931$). The plot shows that the lines for low (pink) and high (gold) income individuals are nearly parallel, with substantially overlapping confidence ribbons, suggesting that income does not moderate the relationship between screentime and positive affect. This is consistent with the insignificant income × within-person screentime interaction in the random-slope model (b = −0.164, p = .448).

Figure 6

a) Within-Person Association of Screentime and Positive Affect b)Within-Person Reactivity of Positive Affect to Screentime Across Trait Income



Note. a) Each gray line represents an individual's within-person association between screentime and positive affect. b) The slope of the lines in this plot represents the degree of within-person reactivity of positive affect to fluctuations in screentime.

Model Results Summary

The multilevel results suggest that within-person fluctuations in health behaviors are more predictive of positive affect than between-person differences. Specifically, increases in physical activity ($p < .001$), sleep quality ($p < .001$), and alcohol use ($p = .020$) relative to an individual's own baseline were associated with higher positive affect, whereas wellness app use ($p = .189$) and screen time ($p = .931$) showed no significant associations. Sleep quality was the only predictor demonstrating both significant between-person ($p < .001$) and within-person ($p < .001$) effects. Additionally, income did not moderate any of the observed relationships, indicating that these patterns were consistent across socioeconomic groups (all interaction terms, $p > .05$).

The findings indicate that daily behaviors like physical activity, sleep, and drug use were linked to changes in positive affect, while screen behaviors were not. However, the models do not explain why these relationships occur, nor do they capture the contextual or subjective experiences underlying these behaviors. The lack of evidence that these individuals' digital behaviors (wellness app use and screen time) were related to their positive affect points to the need to explore the *specific types* and *context* of digital engagement. These gaps motivate the need for qualitative analysis, which can provide a more nuanced understanding of digital engagement.

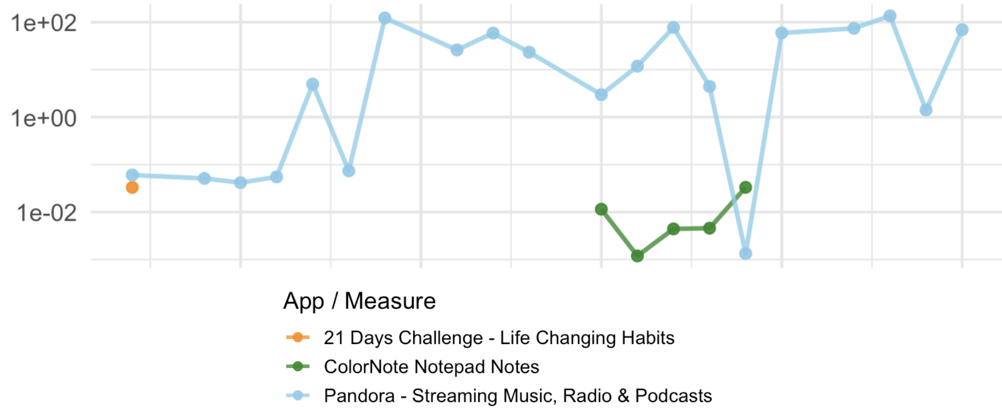
Qualitative Analyses of Individual Vignettes

Participant A

Participant A is a multi-racial female in her late 20s who had a strong positive correlation between the ratio of time she spent on wellness apps and positive affect ($r = 0.49$). Three of the wellness apps she spent time on included "21 Days Challenge - Life Changing Habits," a mental health & wellness app, "ColorNote Notepad Notes," a coloring stress-relieving app, and "Pandora." Her use of these apps fluctuated considerably throughout the study period, with only Pandora being used for the entire period (Figure 7). Despite the moderately strong correlation between her positive affect and wellness app use ratio, the relationship was not consistent over time. Her wellness app use ratio fluctuated throughout the study period, at times corresponding to fluctuations in positive affect, but showed no clear pattern at other times (Figure 8).

Figure 7

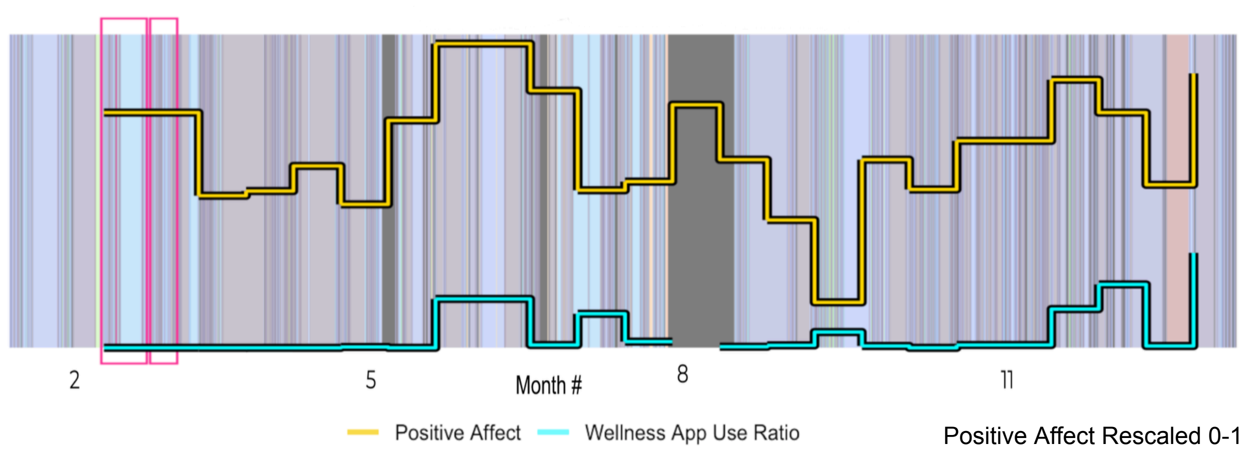
Time Spent on Apps



Note: This plot displays the time (log scale, minutes) spent on wellness apps across the study period

Figure 8

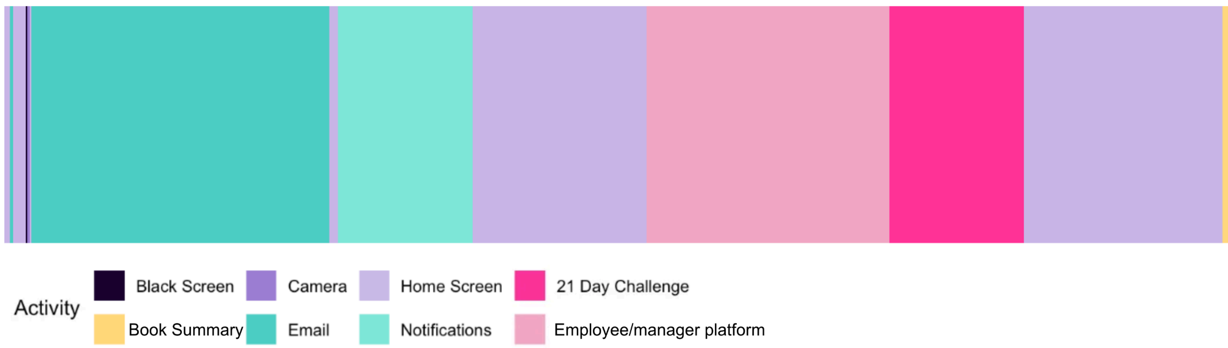
App Usage (Year) with Positive Affect and Wellness App Use Ratio



Note: This plot displays the sequence of app usage for participant A across the year, where each bar represents an app. Lines for Positive Affect (gold) and Wellness App Use Ratio (cyan) are overlaid, and pink boxes highlight the days where the 21-Day Challenge app was used. Positive Affect is rescaled to 0-1.

Figure 9

App Usage Segment Participant A – Total duration: 4345 seconds (72.4 minutes)



Note: This plot depicts a sequence of app usage on a specific 72-minute segment. Each bar represents the instance and duration of app usage within the segment.

Figure 9 shows a segment from a day in the participant's Screenome. The specific date was chosen from a fortnight of Screenome in which the participant used "21 Days Challenge - Life Changing Habits," an app intended to be used for mental health and wellness tracking, and a slight peak in positive affect.

The segment begins with the participant spending 20 minutes checking her email and completing life-management tasks before returning to her home screen. She then opens a secure employee and manager self-service platform and spends 15 minutes onboarding. Next, she opens "21 Day Challenge." She is currently on a structured plan within the app. She spends approximately 10 minutes there, filtering through several "challenges," including reading affirmations & completing a gratitude practice. After closing this app, she opens an app designed to provide quick non-fiction book summaries.

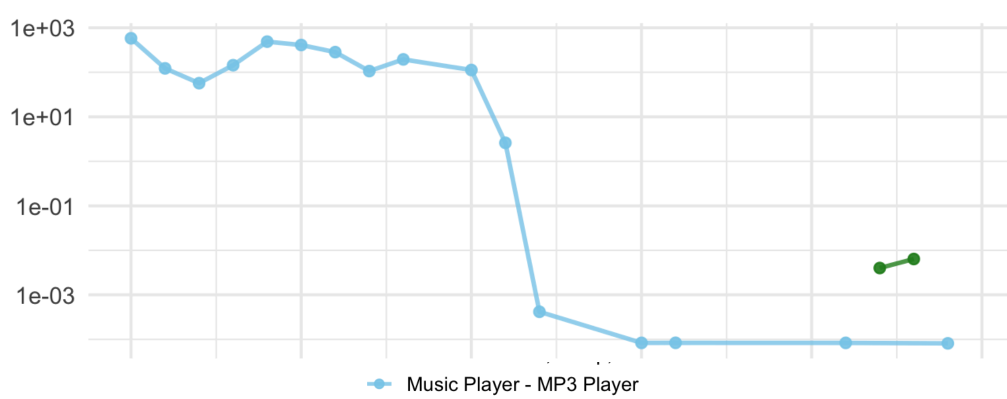
In this segment, Participant A engaged in a sequence of task-driven (rather than passive) digital behaviors. She began with work-related tasks and then transitioned into wellness practices. Participant A is “productive” during the entirety of this segment and engages with wellness app use in the context of a productive, goal-directed behavioral sequence.

Participant B

Participant B is a Hispanic female in her 30s who had a strong negative correlation between the ratio of time she spent on wellness apps and positive affect (r = -0.55). Two of the wellness apps she spent time on included “Calm- Meditate, Sleep, Relax,” a mental health, sleep, and wellness app, and “Music Player - MP3 Player,” an audio app for music and podcasts. Her use of Music Player dropped suddenly halfway through the study period, and she only used Calm near the end of the study period (Figure 10). Despite the strong negative correlation between her positive affect and wellness app use ratio, the relationship was not consistent over time. Her wellness app use ratio fluctuated throughout the study period, at times exhibiting a negative correlation with fluctuations in positive affect, while showing no clear relationship at other times (Figure 11).

Figure 10

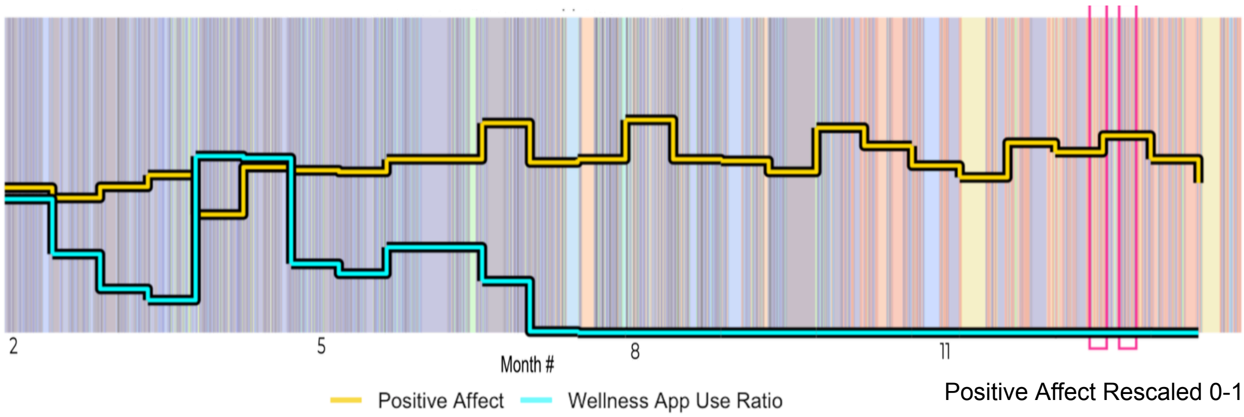
Time Spent on Apps (log scale, minutes)



Note: This plot displays the time (log scale, minutes) spent on wellness apps across the study period

Figure 11

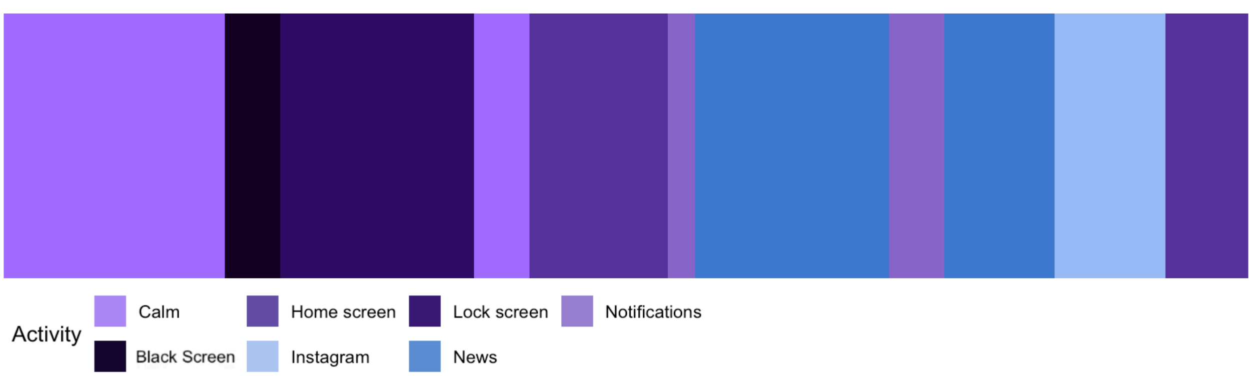
App Usage (Year) with Positive Affect and Wellness App Use Ratio



Note: This plot displays the sequence of app usage for participant B across the year, where each bar represents an app. Lines for Positive Affect (gold) and Wellness App Use Ratio (cyan) on a 0-1 scale are overlaid, and pink boxes highlight the days where CALM was used.

Figure 12

App Usage Segment Participant B – Total duration: 225 seconds (3.8 minutes)



Note: This plot depicts a sequence of app usage on a specific 4-minute segment. Each bar represents the instance and duration of app usage within the segment.

In Figure 12, we see a segment of a fortnight chosen due to the use of "calm," an app intended to be used for mental health and wellness, and a slight peak in positive affect.

At night, the participant sets her alarm on CALM for 5:10 am. CALM is a popular mental health app designed to help manage stress, improve sleep, and build healthy habits. The next screen behavior observed is the participant unlocking her screen in the morning. She opens the bedtime tab in CALM but spends only ~10 seconds there before navigating to her home screen. She then engages in several short behavioral segments, including checking notifications, viewing COVID death news for her county, opening Instagram, and returning to her home screen.

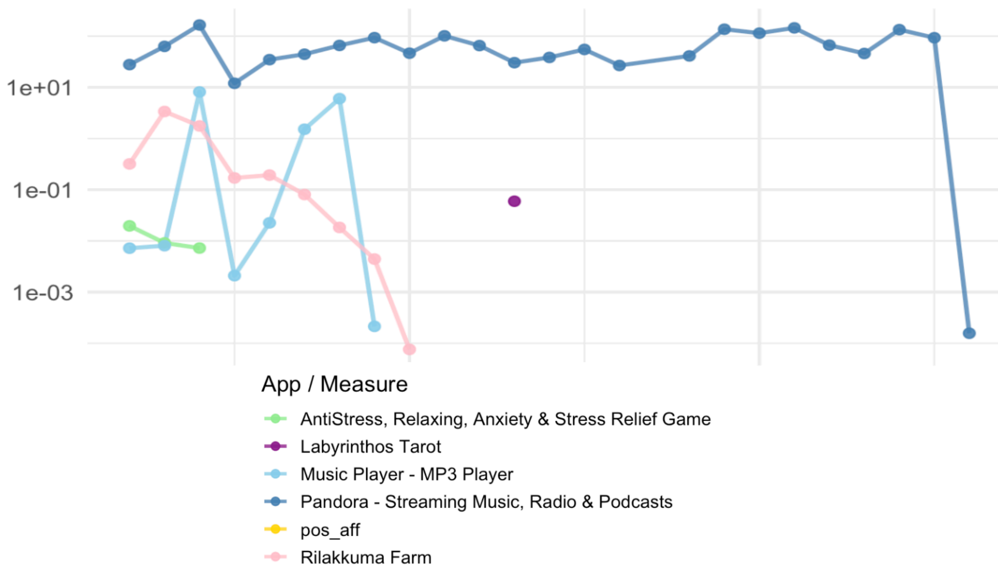
Participant B momentarily engages with an app that could be used for wellness, leading to a sequence of distracted media use. Her wellness use is unsustained and does not suggest goal-directed wellness behavior.

Participant C

Participant C is a White female in her early 20s who had a weak positive correlation between the ratio of time she spent on wellness apps and positive affect ($r = 0.11$). Some of the wellness apps she spent time on included “AntiStress, Relaxing, Anxiety & Stress Relief Game,” a stress-relief game app, “Labyrinthos Tarot,” a spirituality app, and “Music Player - MP3 Player,” an audio app for music and podcasts. She only used these three apps during the first half of the study period, and the time she spent on each fluctuated substantially (Figure 13). Her wellness app use ratio was relatively stable throughout the study period, showing no clear relationship to positive affect (Figure 14).

Figure 13

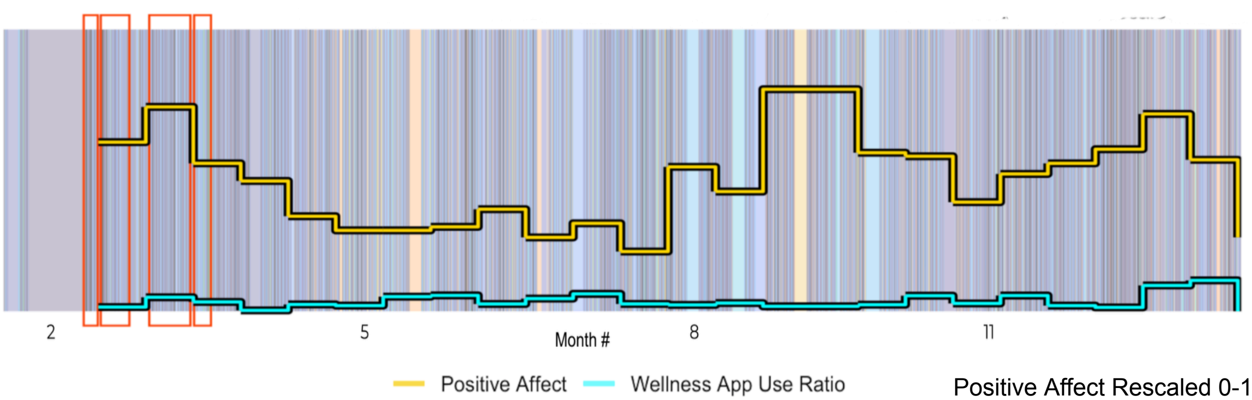
Time Spent on Apps (log scale, minutes)



Note: This plot displays the time (log scale, minutes) spent on wellness apps across the study period.

Figure 14

App Usage (Year) with Positive Affect and Wellness App Use Ratio

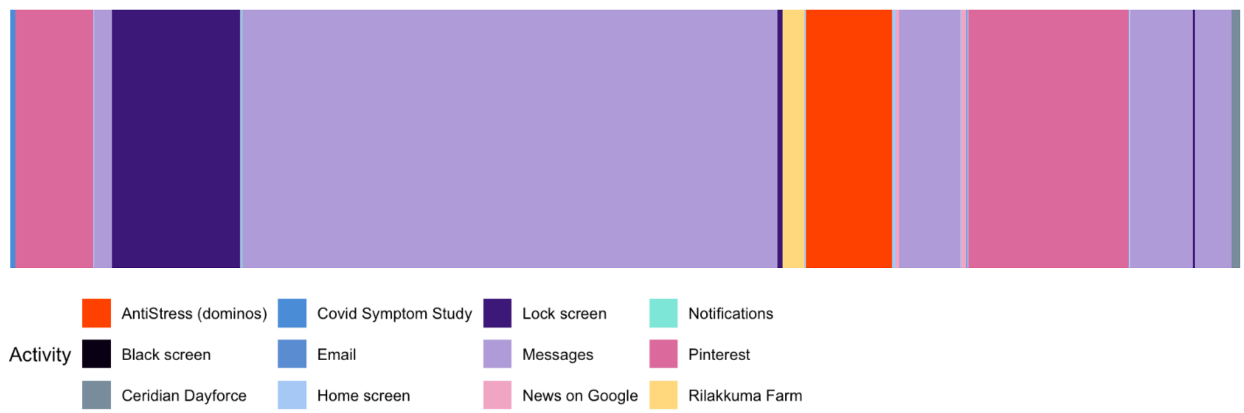


Note: This plot displays the sequence of app usage for participant C across the year, where each bar represents an app. Lines for Positive Affect (gold) and Wellness App Use Ratio (cyan) on a

0-1 scale are overlaid, and red boxes highlight the days where "AntiStress, Relaxing, Anxiety & Stress Relief Game" was used.

Figure 15

App Usage Segment Participant C – Total duration: 4613 seconds (76.9 minutes)



Note: This plot depicts a sequence of app usage on a specific 77-minute segment. Each bar represents the instance and duration of app usage within the segment.

Figure 15 shows a segment from a specific date in a fortnight chosen due to a slight peak in positive affect and the participant's use of wellness-related applications, including AntiStress, Relaxing, Anxiety & Stress Relief Game, an app in which users can select from a variety of anti-stress games including digital versions of sensory games such as fidget spinners and bubble wrap, calming tasks such as cleaning dirty windows and painting fences, and classic puzzles such as rubix cube and tic tac toe. The segment begins with the participant doing a quick Covid Symptom Study before spending time on Pinterest viewing cake-making videos. She then converses with a colleague and checks her texts and notifications periodically over the next few minutes, awaiting a response from her colleague and a potential love interest until her colleague responds. The participant then briefly plays the game "Rilakkuma Farm," a relaxing farming, cooking, and town-building game with an adorable, "kawaii" aesthetic. When she returns to her home screen, the calendar widget shows an upcoming work shift. She then opens the AntiStress app and plays the dominoes game for several minutes.

The participant then moves through Google News, messages, and to email, each for a short period before engaging in a Pinterest scrolling session. Toward the end of this vignette, she engages in multiple text exchanges with a third person and repeatedly checks for texts from the romantic interest. After receiving no reply, she sends follow-up texts. The segment ends with the participant opening a work app to check her work schedule.

This segment begins with a goal-directed activity, but Participant C engages in both passive (e.g., Pinterest scrolling, news browsing) and directed (e.g., Covid Symptom Study, texting, work-related communication) activities. She also repeatedly checks messages and notifications, suggesting potential anticipation or preoccupation with others' responses.

She engages with the AntiStress app for an extended period, which could suggest an attempt to self-regulate emotions or manage stress, perhaps to prepare for offline demands (e.g., upcoming work shift). Overall, this sequence suggests somewhat goal-directed, but fragmented phone usage patterns, characterized by frequent task-switching and social monitoring.

Participant D

Participant D is a White female in her mid-30s who, despite being among the group of high-wellness app usage participants, showed virtually no correlation between the ratio of time she spent on wellness apps and positive affect ($r = -0.01$). Some of the wellness apps she spent time on included “24GO by 24 Hour Fitness” and “Beachbody On Demand - The Best Fitness Workouts,” both fitness apps, and “ColorNote Notepad Notes,” a coloring stress-relieving app.

She used these two fitness apps throughout the study period and used other fitness apps during the year as well, although her usage time fluctuated heavily (Figure 16). Her wellness app use ratio was practically stable throughout the study period, showing no clear relationship to positive affect (Figure 17).

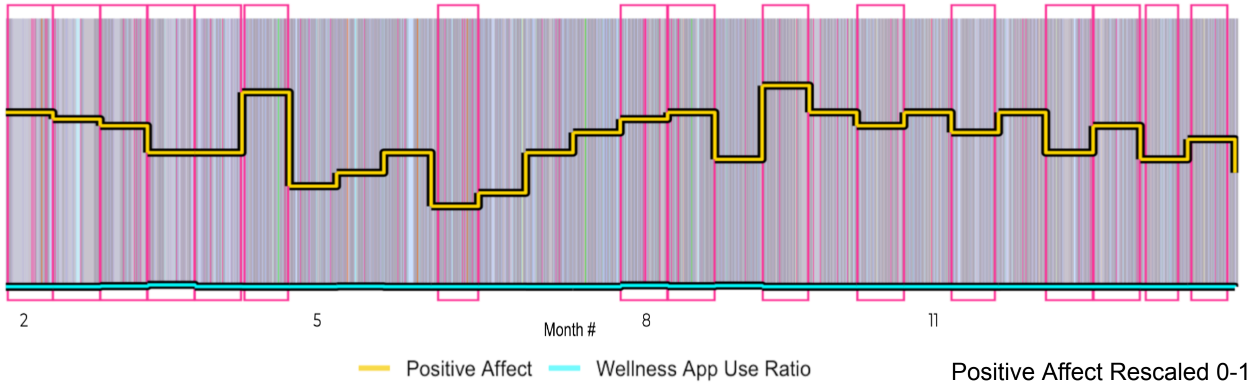
Figure 16

Time Spent on Apps (log scale minutes)

Note: This plot displays the time (log scale, minutes) spent on wellness apps across the study period

Figure 17

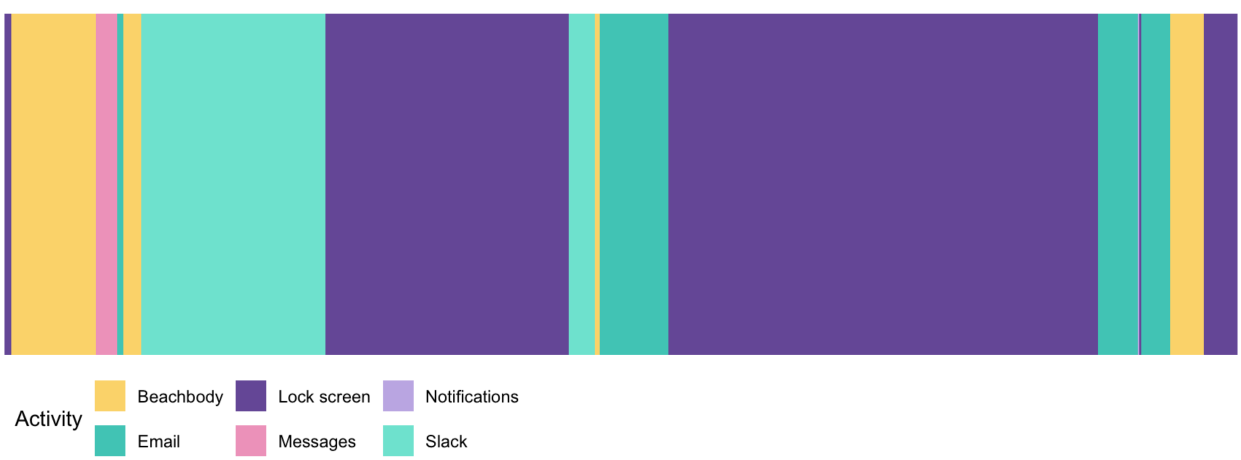
App Usage (Year) with Positive Affect and Wellness App Use Ratio



Note: This plot displays the sequence of app usage for participant D across the year, where each bar represents an app. Lines for Positive Affect (gold) and Wellness App Use Ratio (cyan) on a 0-1 scale are overlaid, and pink boxes highlight the days where "Beachbody On Demand - The Best Fitness Workouts" was used.

Figure 18

App Usage Segment Participant D – Total duration: 3845 seconds (64.1 minutes)



Note: This plot depicts a sequence of app usage on a specific 64-minute segment. Each bar represents the instance and duration of app usage within the segment.

Figure 18 visualizes a segment s from a specific date in a fortnight chosen due to the use of “Beachbody On Demand - The Best Fitness Workouts,” an app designed for community interaction and fitness tracking, “Achievement Rewards for Health,” a rewards program that lets you earn points for everyday healthy actions, such as walking, logging meals, tracking sleep, or answering health surveys, and a mobile portal that allows patients to manage their health care and insurance online, as well as a slight peak in positive affect. This vignette starts with the participant unlocking her phone and navigating to Beachbody On Demand - The Best Fitness Workouts. She is following a three-week fitness plan on this app. She spends time going through different tabs in the app, including responding to a discussion thread about goals, posting recipes, looking at others’ posts, and reviewing her accomplishments on the app's “tracking” tab. All language on the app is encouraging, as are the comments from fellow users.

Prompted by her notifications, she quickly navigates to her texts to communicate with her realtor for approximately 1 minute, then spends less than 1 minute on her email before returning to the Beachbody App for another minute to check reactions to her posts. Finally, she navigates to Slack, where she spends approximately 10 minutes participating in a discussion thread before turning her phone off again.

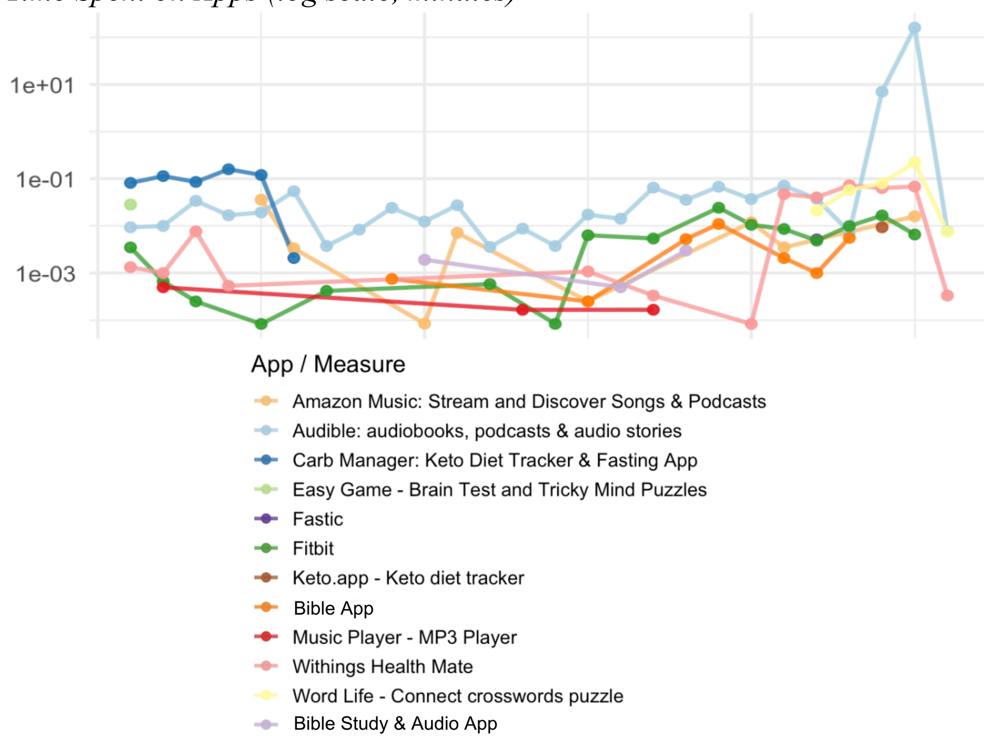
Participant D seemed to open her phone with the intent to navigate to a fitness app and spent time interacting with its content. She was then prompted by notifications to interact with other content on her phone, but still chose to return to her fitness app’s community platform when she was notified of other users’ engagement. This sequence suggests a purposeful, driven, and community-based engagement. Her engagement with wellness behaviors extended to offline practices, including preparing nutritious meals.

Participant E

Participant E is a White male in his late 60s who showed a modest positive correlation between the ratio of time he spent on wellness apps and positive affect (r = 0.27). Some of the wellness apps he spent time on included "Amazon Music: Stream and Discover Songs & Podcasts," a music and podcasts audio app, several religiosity apps, and "Cart Manager: Keto Diet Tracker & Fasting App," a nutrition app. He used several of these apps throughout the study period, although his usage time fluctuated heavily (Figure 19). His wellness app use ratio was essentially stable throughout the study period, with a slight increase near the end that showed no clear relationship to positive affect, although positive affect was also relatively stable (Figure 20).

Figure 19

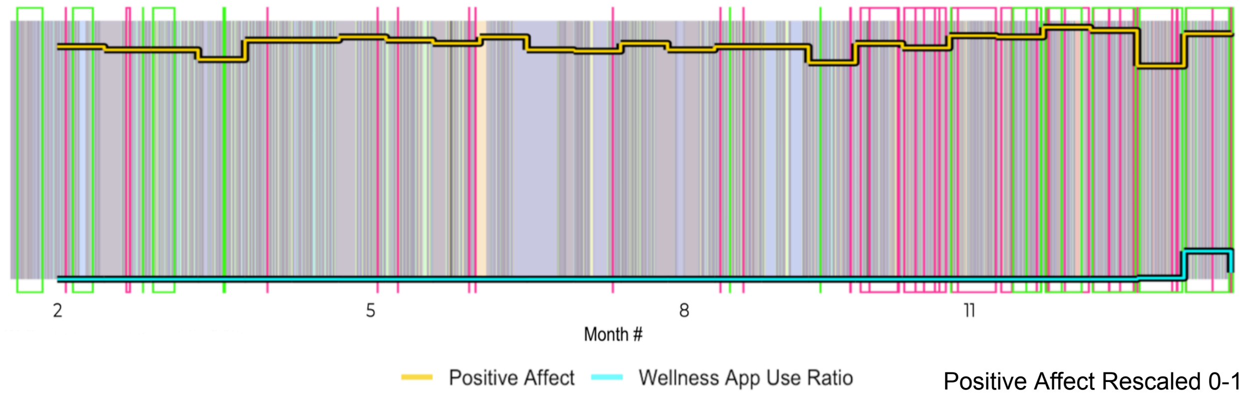
Time Spent on Apps (log scale, minutes)



Note: This plot displays the time (log scale, minutes) spent on wellness apps across the study period

Figure 20

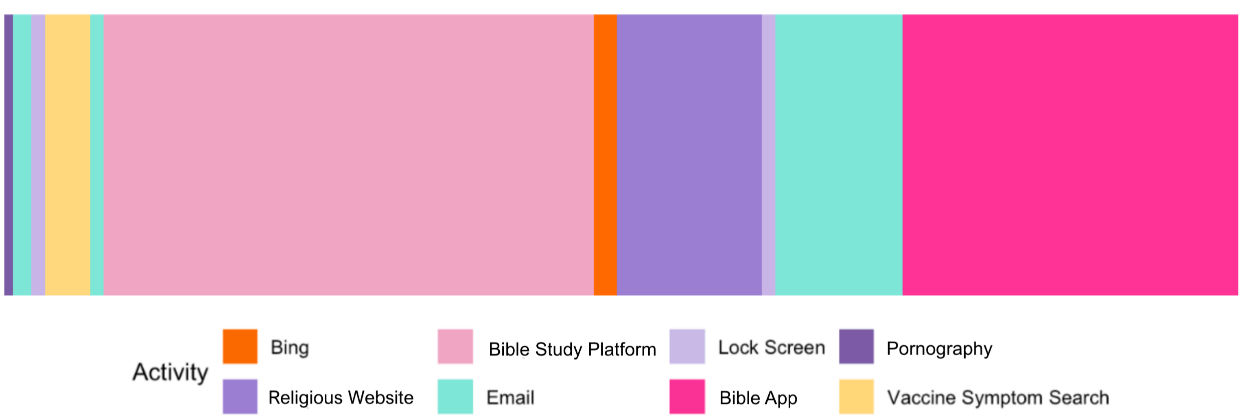
App Usage (Year) with Positive Affect and Wellness App Use Ratio



Note: This plot displays the sequence of app usage for participant E across the year, where each bar represents an app. Lines for Positive Affect (gold) and Wellness App Use Ratio (cyan) on a 0-1 scale are overlaid. Pink boxes highlight the days when Bible-study apps were used, and Green boxes highlight the days when food-tracking apps were used.

Figure 21

App Usage Segment Participant E – Total duration: 1360 seconds (22.7 minutes)



Note: This plot depicts a sequence of app usage on a specific 23-minute segment. Each bar represents the instance and duration of app usage within the segment.

Figure 21 visualizes a segment from a specific date in a fortnight chosen because of the use of several faith and spirituality apps, one of the categories within the mental-health and wellness apps, and a slight dip in positive affect. This segment begins with the participant viewing male-male adult pornography. They then spend little time on their email and Google search before shifting to religious content, visiting online platforms where they read materials focused on sin and salvation, and listening to an audio of a sermon focused on resisting temptation and sin. Next, the participant used a Bible study platform, viewing several study resources, such as Bible commentaries and sermons. Finally, the participant ordered several Bible study resources on a bible app, including resources for asking questions and having successful group discussions.

Participant E engaged with multiple religious and study resources for an extended period, exhibiting sustained, structured digital wellness behavior. His sequence of behaviors, going from viewing explicit sexual content to viewing spiritual content with themes of repentance, suggests a purposeful, driven engagement. His engagement with wellness behaviors may or may not have extended to offline practices.

Cross Vignette Themes

Two main themes emerge among the qualitative vignettes. First, they demonstrate the heterogeneity of “wellness behavior” in the screenome. The participants each use wellness apps for different purposes, from mental health and mindfulness, to physical fitness, to stress relief, to religion. Furthermore, the intentionality of each participant differed greatly, ranging from sustained, goal-directed behavior, such as gratitude practices and fitness tracking, to fragmented, perhaps incidental use. Second, the vignettes show that context shapes everything. The bar code plots show that participants engage with wellness apps in both low and high affective states, and even among the five participants selected from a pool with high *relative* wellness app use, the association between wellness app use and positive affect fluctuated greatly over the study period. These patterns show that the relationship between wellness-app use and positive affect is dynamic, not linear. This may be in part because the participants' wellness app use is deeply embedded in their daily life. The vignettes illustrate how wellness behaviors are simply a small part of a sequence of work tasks, notifications, social communication, planning, stressors, and all of the other behaviors participants use their phones for.

Overall, the vignettes demonstrate that what predicts well-being may not be whether someone opens a wellness app, but how, why, and within what behavioral context they use it.

Discussion

With mental health disorders reaching alarming rates in the United States (Reinert, 2025), particularly among low-income individuals (Marbin, 2022; Ridley et al., 2020; Patel et al., 2018; Pickett & Wilkinson, 2010), it is imperative to understand which behaviors may influence our society's well-being (Wilson, 2022; El-Sheikh et al., 2013). At the same time, screen time continues to rise, yet research on its relationship with mental health remains inconclusive (Brinberg et al., 2021; Cerit, 2025; Nagata, 2024).

The present study sought to fill this gap by answering the questions: "What is the relationship between individuals' offline and online wellness behaviors and their positive affect?" and "Does income moderate these relationships?" To do so, it used a mixed-methods approach examining five behaviors, sleep quality, physical activity, alcohol consumption, screen time, and wellness app use, and their associations with positive affect across socioeconomic groups. Multilevel modeling of self-report and smartphone screenome data from 60 participants quantified between-person and within-person associations between each behavior and positive affect. Qualitative vignette analysis of five participants provided a holistic view of participants' screen behavior and revealed the heterogeneity of wellness behaviors in daily life.

Initial data exploration revealed no significant income-related patterns in overall wellness behaviors or positive affect, and thus not supporting our initial hypotheses. However, higher-income individuals exhibited less variation across all predictor variables.

Further analysis, accounting for individual fluctuations in behavioral predictors and outcomes, revealed that people who engaged in more wellness behaviors, on average, did not report significantly higher positive affect than those who did not, contrary to our initial hypotheses. This between-person relationship was not significant for all study predictor variables except sleep, in which the groups that slept more on average also reported higher positive affect. However, when individuals engaged in more physical activity or had higher-quality sleep than *their personal average,* this led to significant increases in their positive affect. On days in which individuals consumed more alcohol than their personal usual, they also reported higher positive affect, countering our hypothesis but perhaps supporting evidence that alcohol consumption is associated with momentary improvements in happiness (Geiger & MacKerron, 2016). Importantly, neither daily fluctuations in screentime nor wellness-media use were significantly associated with positive affect (not significant).

Furthermore, income level did not moderate participants' affective responses to fluctuations in any of the behaviors studied.

Qualitative analysis of Screenome data allowed for deeper insight into individual patterns of screen use, offering a nuanced understanding of digital wellness behaviors. The five participants' distinct goals and intentionality regarding wellness app use added color to the heterogeneity of digital engagement and screentime effects observed in prior research (Nagata, 2024; Brinberg, 2021; Nakshine, 2022). Additionally, the wide variation in behavioral sequences and affective states within which participants used wellness apps highlighted the importance of context when examining affective and behavioral data.

Significance and Application

The observed relationships among physical activity, sleep quality, and positive affect support the mounting evidence that these wellness behaviors are practical ways to improve mental health (Mahindru, 2023; Palmer, 2023). Sleep stood out as a particularly important behavior, with improved sleep quality having a strong positive association for both between-person and within-person differences. Interestingly, for physical activity, this positive effect applied only to within-person increases, suggesting that it is much more important for individuals to improve their individual wellness habits than to compare their habits to population averages. These results also begin to support the key finding of this study: "*wellness*" is truly an individual matter.

This study's examination of digital behavior addresses a current gap in our understanding of how *specific types* of digital engagement impact affective states. By focusing on digital wellness behaviors and accounting for other wellness practices, demographic characteristics, and broader life context, we discover that the effects of digital engagement on well-being are person-specific and may not be generalizable.

Health and Wellness apps are marketed and perceived as tools to improve well-being, and in some cases, they do so (Lee et al., 2024). This framing makes the insignificant relationship between wellness app use and positive affect particularly interesting. The qualitative vignettes helped contextualize the insignificant relationship between wellness app use and positive affect, painting a picture of the vast variation in how users move in and out of wellness apps. They also add color to the wide range of motivations behind wellness app use, such as distraction, reflection, and self-improvement, suggesting that users' life contexts and intentions may matter more than the app itself. The vignettes once again make it clear that *wellness is an individual matter.*

Taken together, the quantitative and qualitative results suggest several implications for the design and evaluation of digital health tools that may help create positive affective responses. First, digital wellness tools should not imply that time spent on their platform will equate to improved mental health without further research and analysis. Second, digital wellness media should strive to take into account the broader life context of the user's engagement. Ideally, apps should take into account users' behaviors outside the app, both online and offline, to create a more personalized experience. Finally, these tools should strive to understand users' intentions, thus taking an individual rather than a prescriptive approach to each user's wellness.

Limitations & Future Directions

There are several limitations to consider. First, it is important to note that the generalizability of these results is limited by the sample population, which consisted of only 60 participants, 67% of whom were male. As such, these findings may not generalize to more representative populations.

Second, key variables are subject to measurement error. Positive affect, sleep quality, physical activity, and alcohol consumption all measured via self-report and may be subject to individual error or bias. The wellness apps categorized for the wellness-app-use variable were classified using a binary question, which may obscure meaningful variation across app types and their effects (e.g. fitness tracker vs meditation app vs religious app).

Finally, the data collection process introduces time-scale limitations. The self-report data were captured fortnightly, thereby missing potential fluctuations in wellness behaviors and positive affect between observations.

Future research should aim to address these limitations. Screenome studies focused solely on wellness media use would allow for larger, more diverse samples, yielding more statistically significant and generalizable results. A larger set of wellness app users would also enable a more nuanced analysis of wellness apps, differentiating by categories, which may reveal category-specific effects that the current study overlooked. Selecting a larger sample for qualitative analysis could also deepen understanding of individualistic patterns in digital wellness behavior and overall media use. Finally, increasing the frequency of self-report measures from fortnightly to weekly or daily could better capture momentary fluctuations in affect and behavior.

Conclusion

This study provides a comprehensive understanding of how online and offline wellness practices jointly shape emotional well-being, and answers the questions: “What is the relationship between offline and online wellness behaviors and positive affect?” and "Does income moderate these relationships?" The results add to the current literature on the effects of wellness behaviors and on the effects of digital behaviors on mental health. Most effects were nonsignificant, including, notably, the effect of digital wellness engagement, suggesting that wellness may not be accurately captured by group-level analysis. The qualitative vignettes shed light on this insight, revealing that user context and intention may matter more than time spent in an app. Together, these findings lead to the conclusion that wellness, and its relationship to digital engagement, is *deeply* individual.

I believe this central point is important to communicate in this age marked by growing mental health concerns (Reinert, 2025) and the complete integration of screens into daily life (Cerit, 2025; Nagata, 2024), particularly given the commonly held belief that screen time is inherently harmful to mental health (K. Kaye et al., 2020). I hope to extend the reach of this work beyond academia through a journalistic-style communication piece that conveys the study's findings in a more accessible and engaging way (Appendix A), informing laypeople, app designers, and researchers alike about the complex nature of wellness and media use.

Although more research is needed, these findings have potentially powerful practical implications for the future of digital wellness tools as a scalable, low-cost method to promote well-being, especially for vulnerable populations that may face barriers to traditional care. However, that requires a shift in how these tools are currently analyzed and designed, away from group-metrics and broad scale trends to accounting for individual users' broader life contexts and engagement intentions. Rather than focusing on averages, future research and products must learn to design for *the one.*

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Appendix A

A Communicative Magazine-style Piece Author Notes:

Why the Transformation?

Enjoy your youth! Now's the time to have fun, do crazy things, and make lasting memories. Now is also the time to move away from your community, plan for your future, form relationships that you will (hopefully) foster forever, and make decisions that could very well impact the rest of your life. It's interesting that early adulthood is seen as the "prime of life," seeing as across all age groups, early adulthood is also the age with the worst mental health (National Institute of Mental Health, 2024).

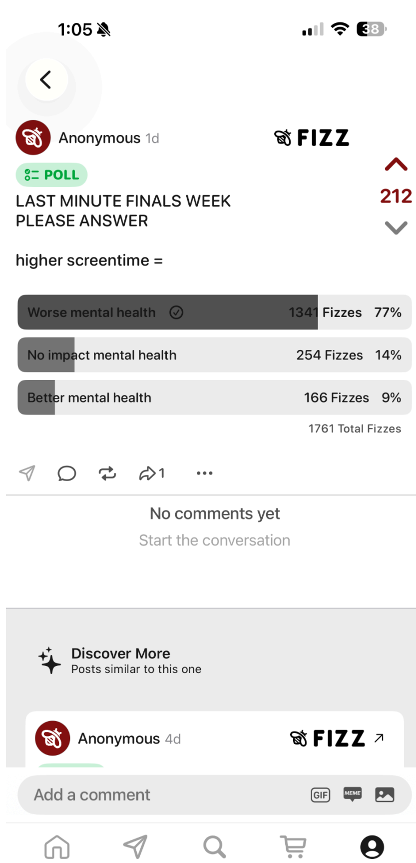
Adolescence and young adulthood are hard periods to navigate. Have they always been? I wonder whether and how the difficulties of adolescence and young adulthood have changed with the rapidly evolving social and technological climate. From the nostalgic 2000s flip-phones to music on iPod touches to now using smartphones for everything, late-night boba orders, seemingly never-ending FaceTime calls, checking health records, and sending last-minute networking emails, this generation of young adults and adolescents has grown up as screens got embedded into nearly every aspect of everyday life.

Smartphone screens have enriched our lives and expanded our worlds, but also made us into test subjects group A: the effects of screens on, well, everything. Now, our use of technology is another thing adding to our adventure-filled obstacle course of life. Humans want to feel and be emotionally *well*, but even in the age of endless accessible knowledge, it can be difficult to know how.

When I began working with The Change Lab at Stanford University, I would have put my name to the claim that screen time is harmful to mental health. However, I have since learned that this claim is not backed by research. The scientific evidence consistently shows mixed or insignificant effects of screen time on well-being.

Research in The Change Lab, including the present study, reveals the heterogeneity in screen use and points to the need to increase the nuance of our study of screentime, differentiating screen use by content type, purpose, and individual intent. These distinctions could clarify when and for whom digital engagement supports or harms emotional well-being.

Although it feels ironic when I hear it from a matcha-loving Instagram influencer life coach, “get on your phone less” seems to be the common rhetoric as a solution to improved well-being. I decided to do a quick test of the salience of this belief at Stanford using a poll on Fizz, an campus-based social media app where students anonymously share posts and questions within their college community. I asked the question “higher screentime = a. worse mental health, b. no impact on mental health, or c. better mental health.”

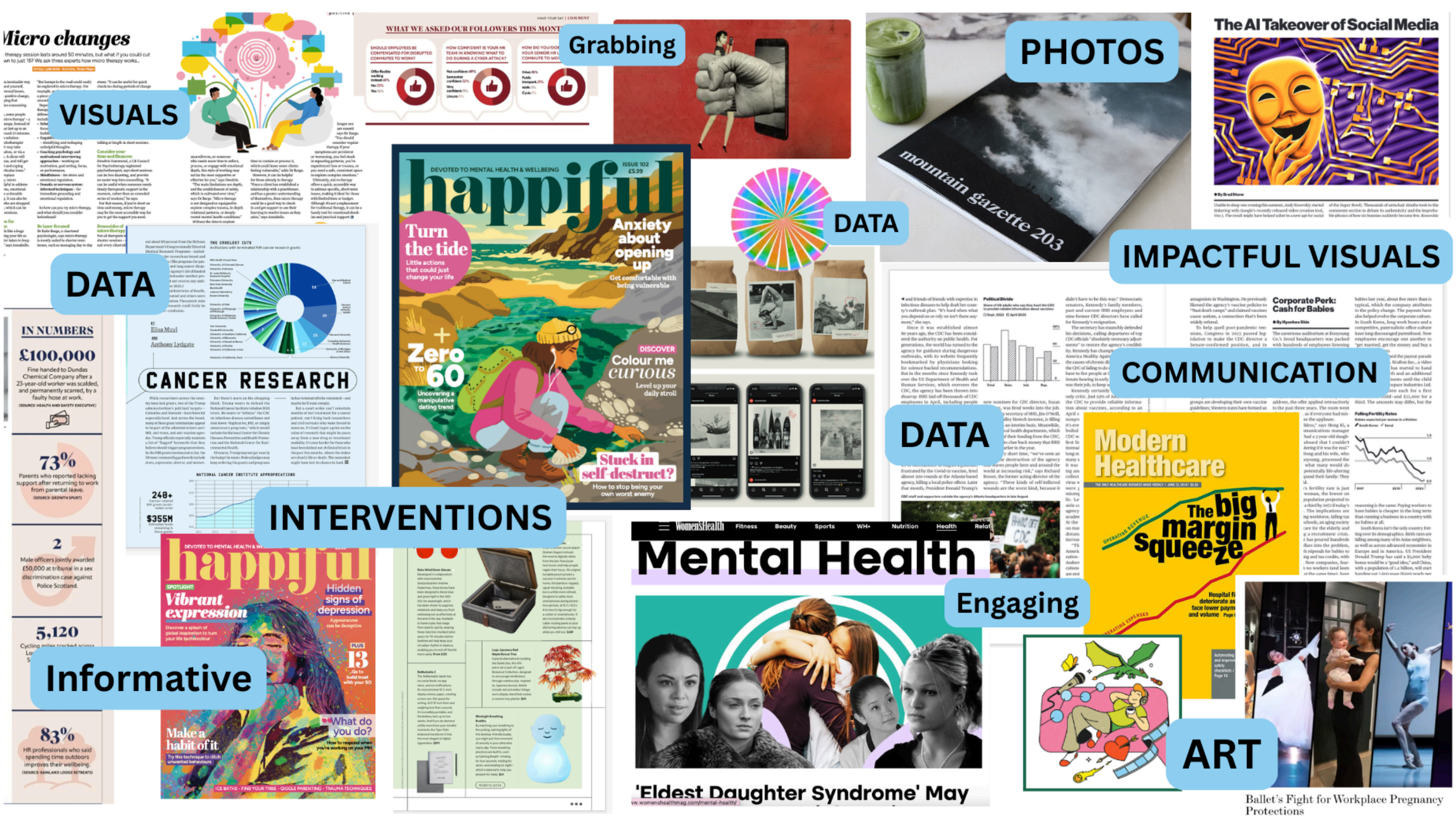


The results, shown in the picture above, indicate that of 1761 Stanford students who voted, 77% endorsed answer choice "higher screentime = worse mental health." We *want* to be *well* while navigating young-adult mayhem, but screens are so deeply intertwined in everything we do. In answering the question, it seems we forget the vast variability in how we use our phones and how they both help and hurt us.

In this study, I add to the Change Lab's research on the more nuanced effects of screentime, examining both offline and online wellness behaviors, how those behaviors are related to fluctuations in individuals' feelings of positive affect, and whether the the associations between wellness behavior and positive affect differ across socioeconomic groups.

Rather than communicate my findings in an academic journal-style paper, which I know an *insignificant* number of my peers will read, I will transform the manuscript below into a magazine-style piece, in hopes that it may reach just a few more individuals as they navigate the *prime of their lives.*

Vision Board for future inspiration:



Appendix B

Descriptives Statistics

Table B1

Descriptive Statistics of Key Variables

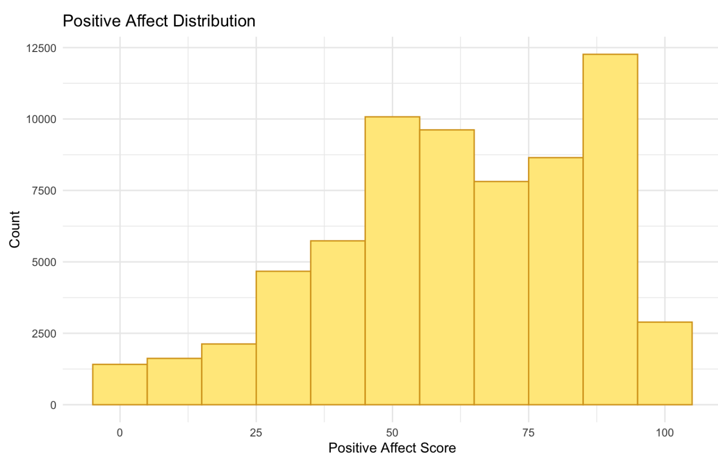
Variable	N	Mean	Median	SD	Min	Max
Positive Affect	66880	62.05	62.50	24.05	0.00	100.00
Physical Activity (minutes)	66880	23.12	20.00	23.60	0.00	120.00
Sleep Quality	66880	66.98	70.00	22.20	0.00	100.00
Alcohol Use	66880	1.44	0.00	4.49	0.00	42.00
Screentime (minutes)	66880	324.90	298.59	168.08	5.81	1022.94
Wellness App Use Ratio	66879	0.01	0.00	0.04	0.00	0.85

Plots

Positive affect, physical activity, sleep quality, and screentime scores were approximately normally distributed. Alcohol consumption and wellness app use ratio scores were each heavily skewed, with most participants reporting 0 drinks consumed per fortnight and a wellness app use ratio near 0.

Figure B1

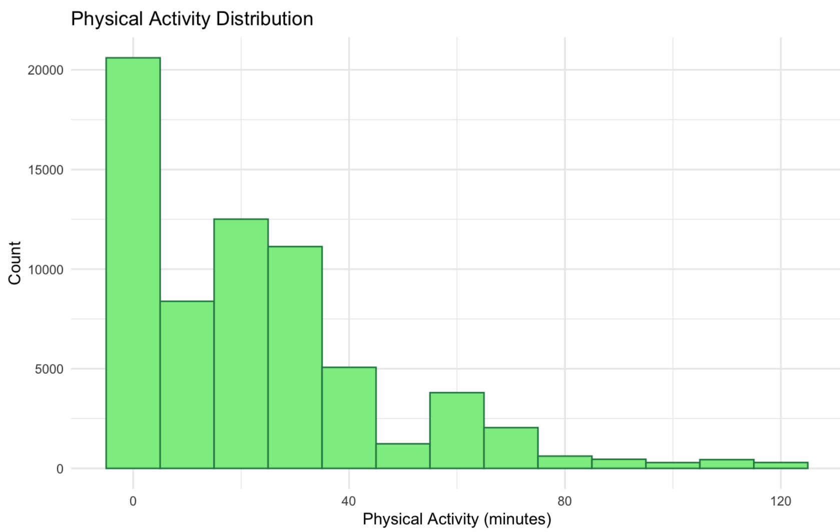
Positive Affect Distribution



Note. Approximately normally distributed with a slight left-skewed and many observations of participants reporting moderately high positive affect on the previous fortnight (peak 85–90).

Figure B2

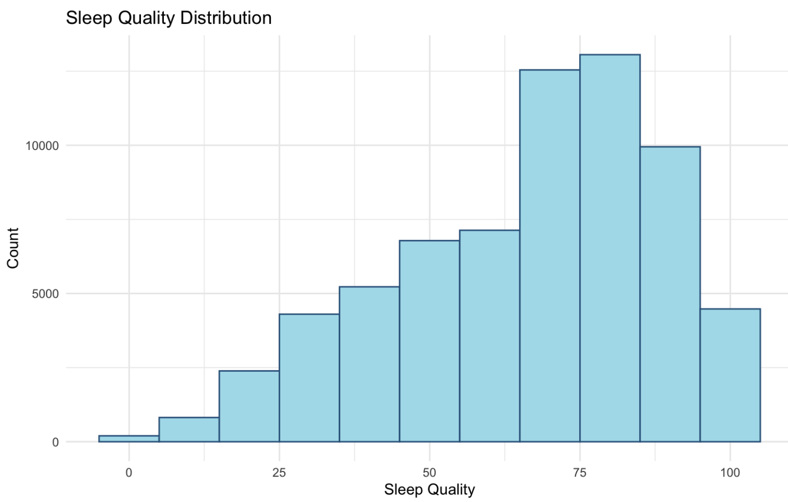
Physical Activity Distribution



Note. Approximately normally distributed but right skewed, with a cluster of observations reporting 0 minutes spent in rigorous physical activity during that fortnight.

Figure B3

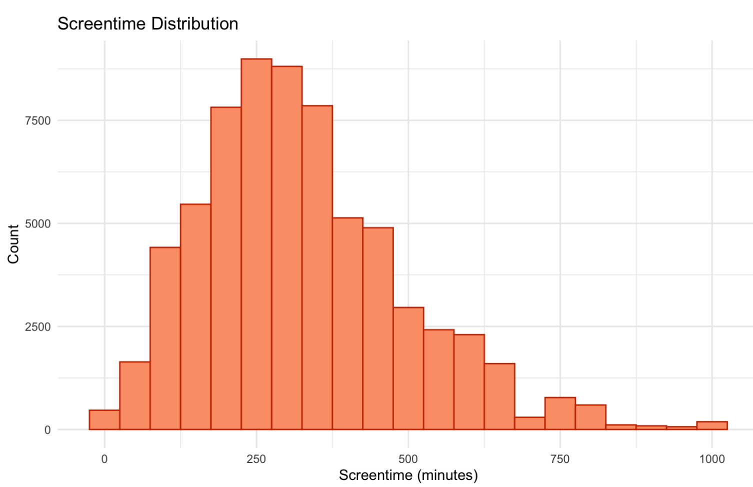
Sleep Quality Distribution



Note. Approximately normally distributed and slightly left-skewed, with over half of observations reporting sleep quality scores higher than 50 and a cluster of observations in the 65-85 range (0-100 scale)

Figure B4

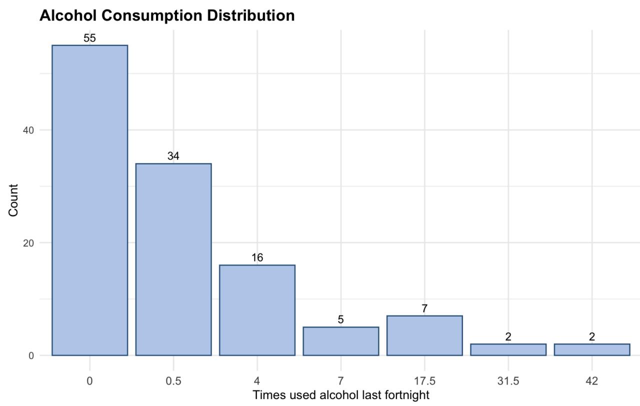
Screen Time Distribution



Note. Normally distributed (mode ~ 250–300 minutes)

Figure B5

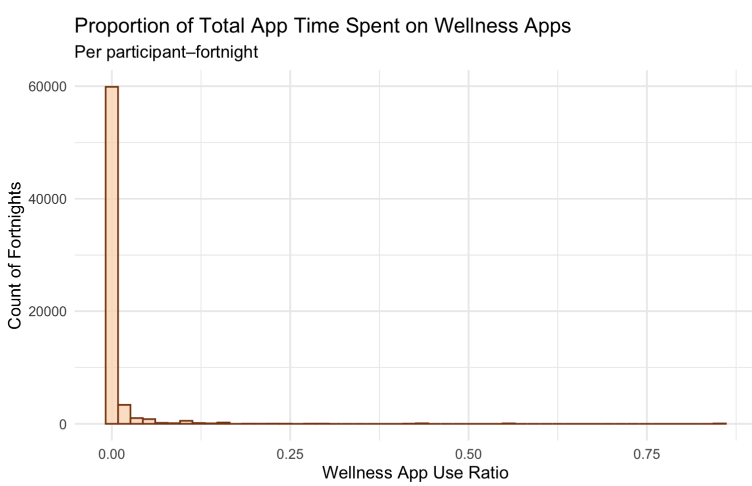
Alcohol Consumption Distribution



Note: Heavily skewed, with most participants reporting 0 drinks consumed per fortnight

Figure B6

Wellness App Use Ratio Distribution



Note: Heavily skewed, with most participants reporting a wellness app use ratio near 0.

Appendix C

Correlations Between Measures

Table C1

Correlations

Variable	*N*	*M*	*SD*	1	2	3	4	5	6
1. Physical Activity (min)	61739	23.86	23.97						
2. Sleep Quality	61739	66.68	22.66	.11**					
3. Alcohol	61739	1.54	4.65	.21**	-.09**				
4. Positive Affect	61739	61.14	24.16	.21**	.51**	-.09**			
5. Screentime (min)	61739	313.65	166.28	-.03**	-.15**	-.05**	-.10**		
6. Income	61739	4.47	2.76	.08**	.02**	.08**	.16**	-.17**	
7. Wellness Ratio	61738	0.01	0.04	.02**	-.05**	-.03**	.00	-.06**	.01

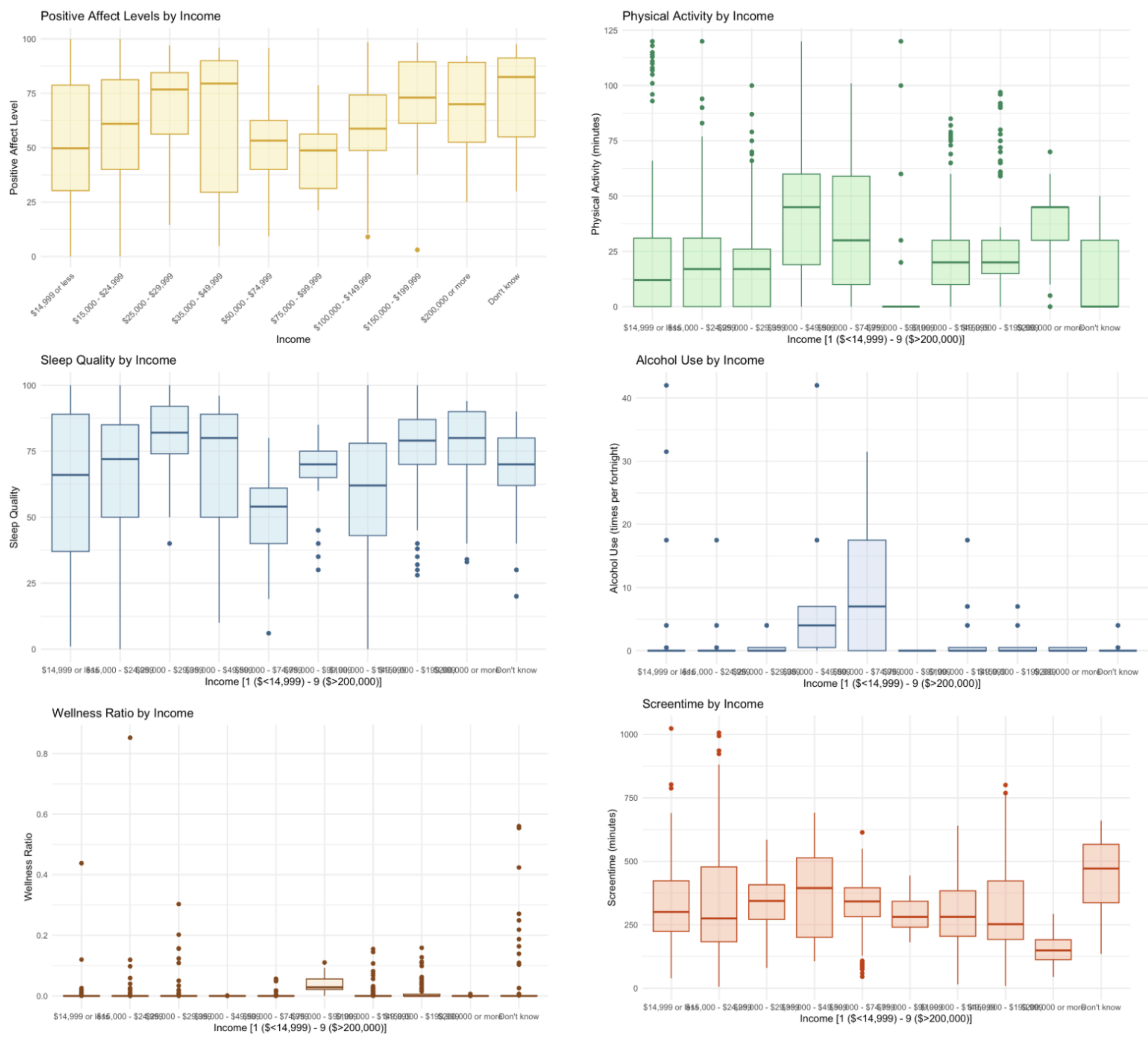
Note. *N* = number of cases. *M* = mean. *SD* = standard deviation. * indicates $p < .05$. ** indicates $p < .01$.

Appendix D

Distributions Across Income Categories

Figure D1

Distribution Across Income Categories



Note. These box plots show there is no consistent income gradient in positive affect, although the lowest income category (0-14999) and the $75k–$99,999 group had the lowest median positive affect (~50). There are also no visible trends across income categories for any of the predictor variables. This may be due in part to the small sample size (n=60). This data does not support the hypotheses that higher-income groups will spend more time on wellness behaviors and exhibit higher positive affect (H 0.1-0.6)

Appendix E

Univariate Analysis *(Between-Person Income and Intraindividual Variability)*

Cross-sectional linear regressions were used to discover whether household income predicted intraindividual variability (iSD) for each study variable.

A. Positive Affect

Income showed the strongest effect on positive affect variability. When income is in the lowest category ($14,999 or less, coded as 1), positive affect variability is 14.32 SD units. For every one-unit increase in income category, variability in positive affect decreases by 0.555 SD units ($b = -0.555$, $t(61737) = -71.64$, p-value: $p < .001$, $R^2 = 7.68\%$) (Figure E1).

B. Physical Activity

Income was negatively associated with physical activity variability. When income is at the lowest category ($14,999 or less, coded as 1), physical activity variability is 14.81 SD units. For every increase in income category, variability in physical activity decreased by 0.204 SD units ($b = -0.204$, $t(61737) = -18.18$, $p < .001$, $R^2 = 0.005$)(Figure E2).

C. Sleep Quality

Income was negatively associated with sleep quality variability. When income is at the lowest category ($14,999 or less, coded as 1), sleep quality variability is 14.46 SD units. For every increase in income category, variability in positive affect decreases by 0.365, SD units ($b = -0.365$, $t(61737) = -47.44$, $p < .001$, $R^2 = 3.52\%$)(Figure E3).

D. Alcohol Consumption

Income showed the weakest negative effect on alcohol consumption variability. When income is in the lowest category ($14,999 or less, coded as 1), alcohol consumption variability is 1.14 SD units. For every increase in income category, variability in alcohol use decreased by 0.024 SD units ($b = -0.024$, $t(61737) = -7.645$, $p < .001$, $R^2 = 0.0009$)(Figure E4).

E. Wellness App Use

Income was negatively associated with wellness app use variability. When income is at the lowest category ($14,999 or less, coded as 1), wellness app use variability is 0.0210 SD units. For every increase in income category, variability in wellness app use decreased by 0.00175 ($b = -0.00175$, $t(61737) = -37.34$, $p < .001$, $R^2 = 0.022$)(Figure E5).

F. Screen Time

Income was negatively associated with screentime variability. When income is in the lowest category ($14,999 or less, coded as 1), screentime variability is 86.72 SD units. For every increase in income category, variability in screentime decreased by 3.048 SD units ($b = -3.048$, $SE = 0.068$, $t(61737) = -44.88$, $p < .001$, $R^2 = 0.032$)(Figure E6),

G. Summary

Overall, the findings supported the prediction (H 0.7) that higher-income individuals report lower affective and behavioral variability, with the strongest effects for positive affect and the weakest for alcohol consumption.

Univariate IIV Metrics Plots

Figure E1

Positive Affect Univariate Plot

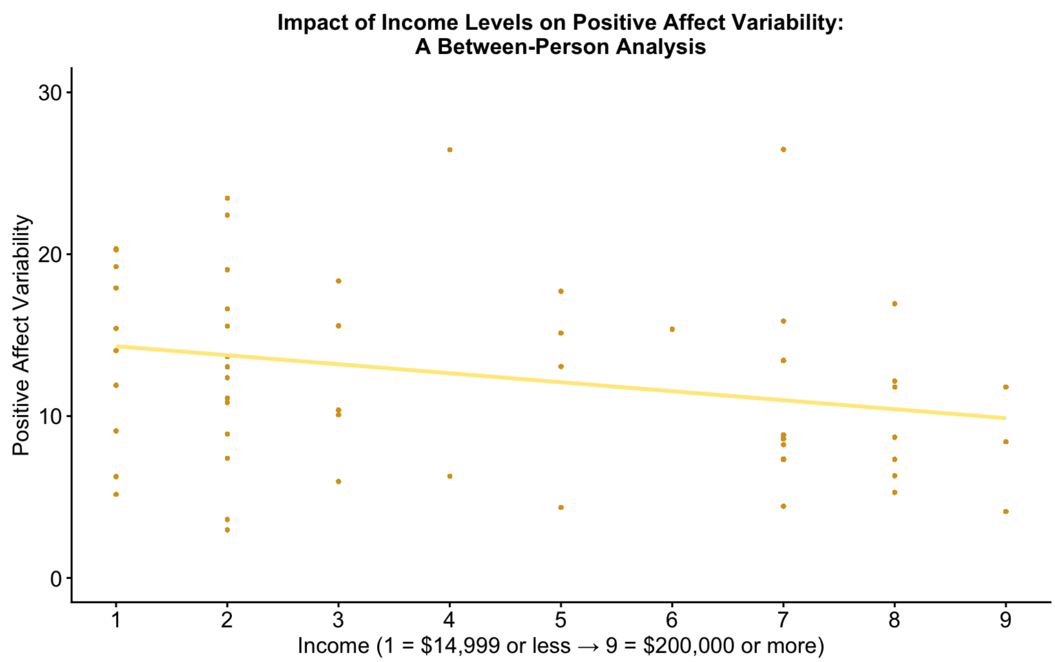


Figure E2
Physical Activity Univariate Plot

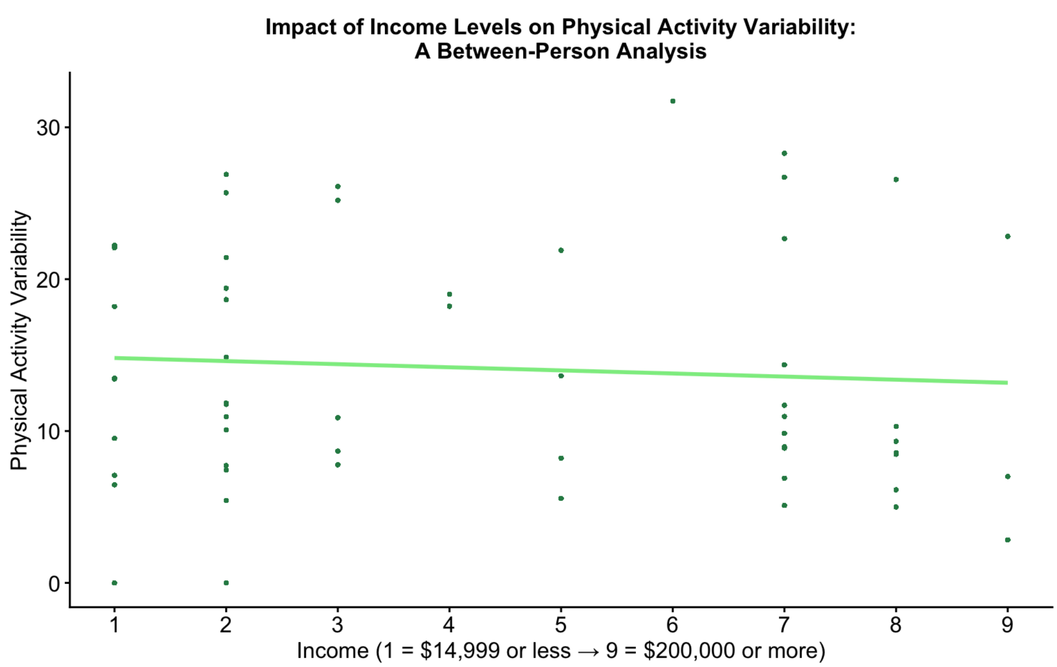


Figure E3

Sleep Quality Univariate Plot

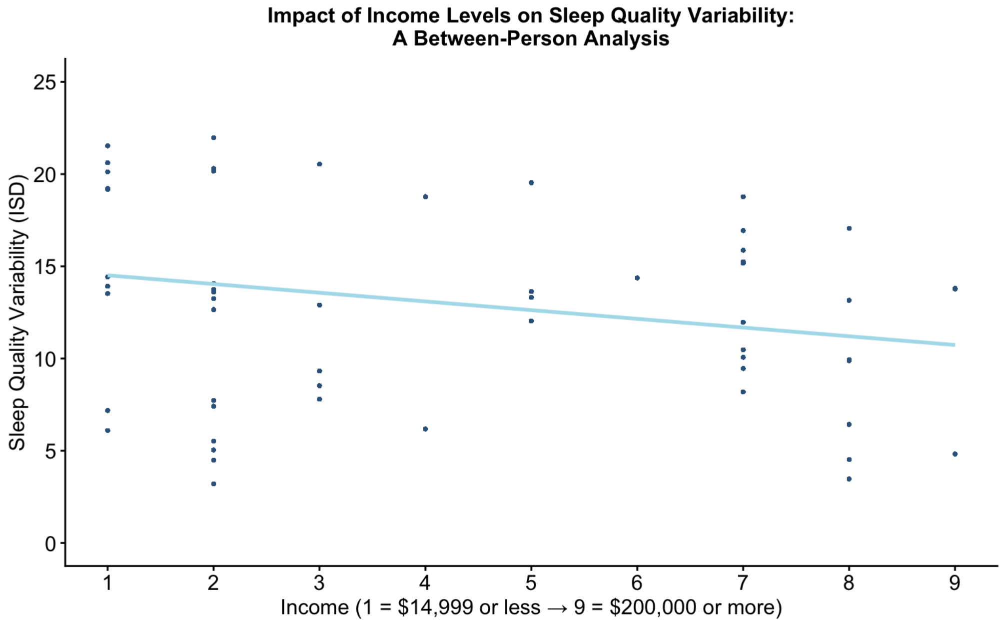


Figure E4

Alcohol Univariate Plot

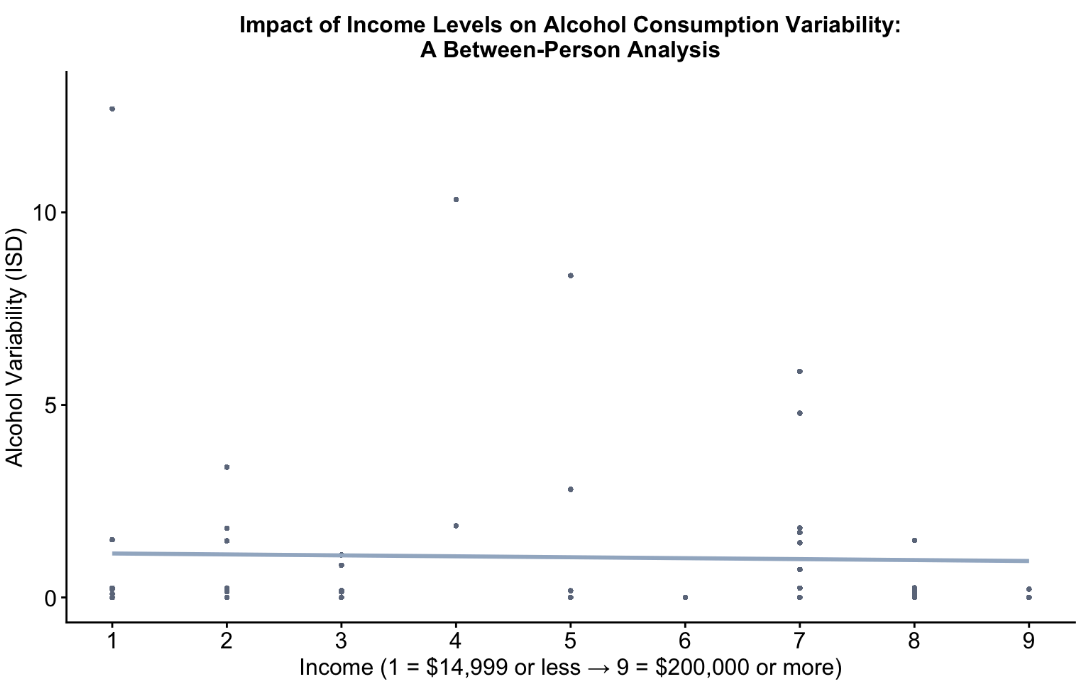


Figure E5

Wellness App Use Ratio Univariate Plot

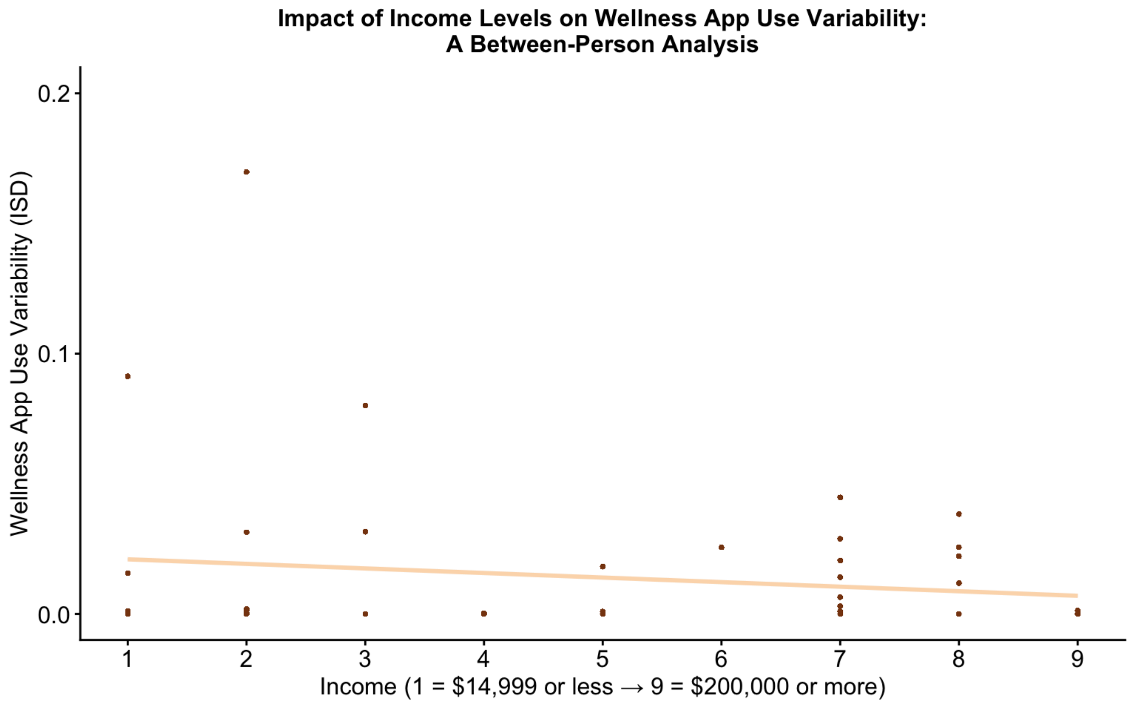
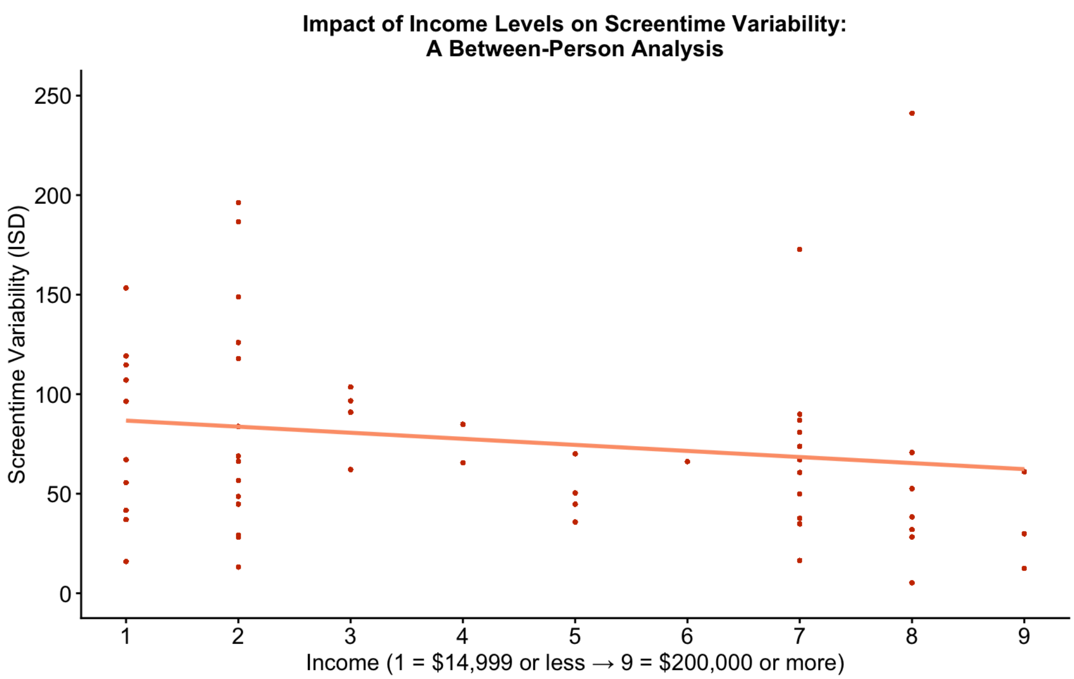


Figure E6

Screentime Univariate Plot



Appendix F

Multilevel Modeling Framework and ICC

Multilevel Modeling Framework

To distinguish between **person-level** and **group-level** differences, positive affect, physical activity, sleep quality, alcohol use, screen time, and wellness app use were separated into two components using a person-mean centering approach (Enders & Tofighi, 2007). The **between-person variable (trait level)** represents each participant's average level of the behavior across the study period, and the **within-person variable (state level)** represents each individual's deviations from their personal average at a given fortnight (State Variable = Observed Score − Person Mean (trait)). Household income was treated as a numeric variable (1–9, excluding "Don't know" responses) and was also person-mean centered for analysis.

Distributions, correlation matrices, and linear association plots were used at the trait and state levels to understand variable distributions and basic associations prior to multilevel modeling.

Intraclass Correlation Coefficient

First, we fit a null model with a random intercept and positive affect as the outcome variable to discover how much variation in positive affect is due to changes within, versus between people.

$$PositiveAffect_{ij} = \beta_0 + u_{0j} + e_{ij}$$

Where:

- i = time point
- j = person

- β_0 = average positive affect
- u_{0j} = person (j) deviation from average
- e_{ij} = within-person fluctuation

The Intraclass Correlation Coefficient (ICC = $\frac{u_{0j}}{u_{0j} + e_{ij}}$) was calculated to quantify this variation, giving us the *percentage* of the total variation in positive affect due to differences between individuals and (if high) giving a metric to justify multilevel modeling.

Multilevel Model

Five separate multilevel models were fit using each predictor variable as the main predictor, income as a person-level predictor, and state positive affect as the outcome. The models also include fortnight as a predictor to control for time-based trends over the study period.

Each predictor variable is decomposed into its between-person and within-person components to capture average levels and day-to-day fluctuations relative to each individual's personal average. Each wellness behavior model is then able to test (1) the between-person effect of the behavior on affect, (2) the within-person effect of the behavior on affect, (3) the moderation of income, and (4) the three-way interaction between within-person and between-person components across income.

Appendix G

App Categorization Survey Questions

1(a). Is this a Communicative app?

Communicative apps refer to apps where users can communicate and exchange information with other users/entities. Users may provide and/or receive information through the app. Communicative apps may or may not have large social networks. Examples include email apps, messaging apps, news media apps, or browsing apps like Safari, Google Chrome, Firefox, etc.

1(b). Is this a Social Media app?

Social media refers to digital platforms and technologies that facilitate the creation, sharing, and exchange of information, ideas, interests, and other forms of expression via virtual communities and networks. Social media platforms enable users to interact with content and other users through posts, comments, likes, shares, and direct messaging. Social media apps include apps that allow users to interact with content, even if users themselves cannot create their own content. Examples include Facebook, Twitter, Instagram, LinkedIn, and TikTok.

2(a). Does the app regularly present content tailored to a user's past behavior and interactions?

Many apps personalize users' experience using algorithms that deliver new content based on a users' past behavior and preferences. Examples of apps that use such algorithms to present content include TikTok, Spotify and YouTube.

2(b). Does the app regularly prioritize showing a user popular or trending content, even when it doesn't align with the user's usual interests?

Many apps personalize users' experience using algorithms that deliver new content based on popular topics and trends. For example X/Twitter's "Trending" section highlights topics or hashtags that are currently popular across the platform.

3(a). Is the purpose of this app to help users cultivate mental health and wellness?

Help-seeking behavior is defined as "*searching for or requesting help from others via formal or informal mechanisms, such as through mental health services.*" We are interested in examining this help-seeking behavior in digital platforms. To do this, I will look at mobile applications for both formal help-seeking behavior (mental health apps) and informal help-seeking behavior (wellness apps). <u>Mental Health mobile applications are mobile applications that help users assess, support, regulate, and treat their mental health. Wellness mobile applications are a broader category and include any mobile applications that aim to help people improve their well-being by promoting healthy habits and lifestyles.</u>

4(a). Is the purpose of this app to display graphic or explicit content to users?

An application built for the purpose of displaying graphic or explicit content. This may include apps with a user rating of 18+, dating apps, pornography apps, violent video game apps, and more. These apps facilitate user's access to and viewing of graphic or explicit content. Apps that are NOT built for the purpose of displaying graphic or explicit content include apps that are specifically built for an age-restricted audience of 12 and under (e.g. YouTube kids) or specifically non-graphic content (e.g. Duolingo, Cash App, Sephora).

4(b). Does this app provide users access to graphic or explicit content?

An application that may provide a user with graphic or explicit content, consensually or non-consensually. Examples may include social media apps, internet explorers, messaging apps, and more.

5(a). Is this app designed to facilitate social interactions or connections between users (e.g., interpersonal relationships, community interaction, social engagement)?.

5(b). Is this app designed to support work-related tasks or professional productivity (e.g., task management, productivity tools, professional networking)?.

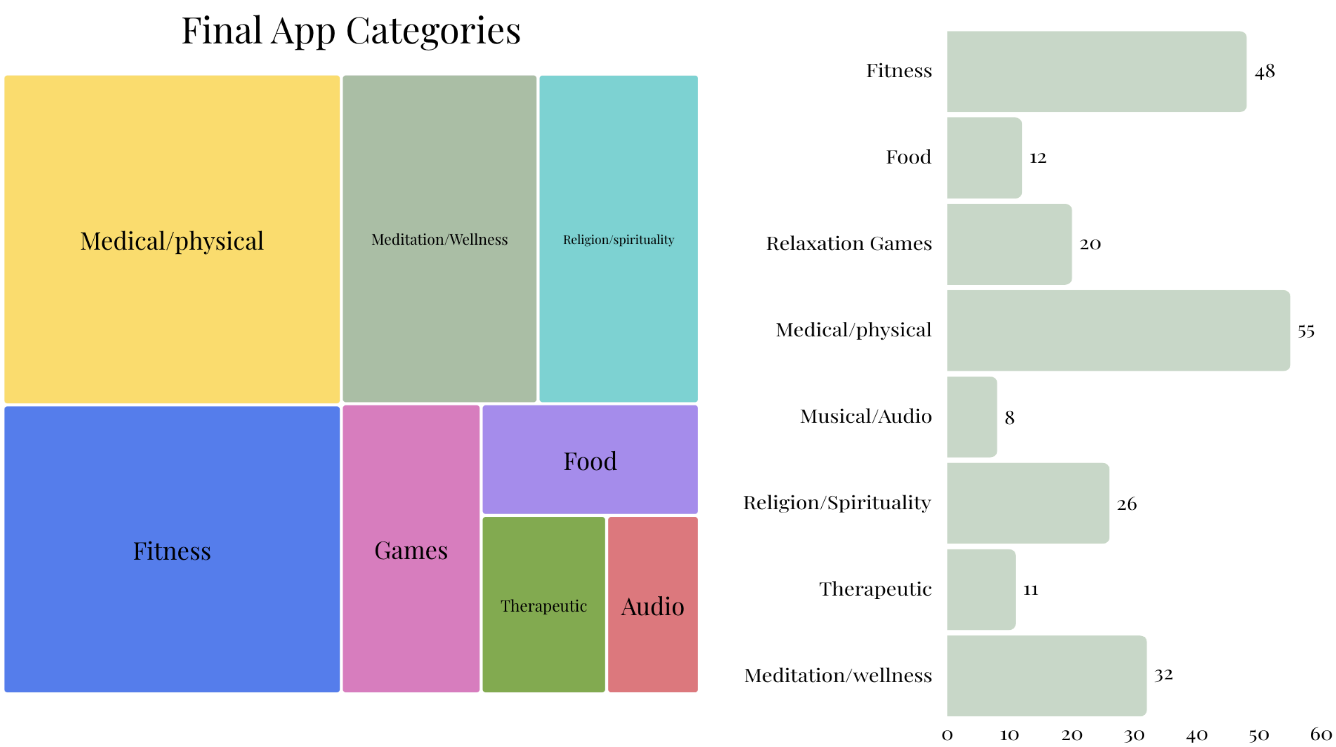
6. If the user encounters faces on this application, are they likely to be familiar (select yes) or non-familiar (select no) faces?

Appendix H

Wellness Apps

Figure I1

App Category Distributions



Appendix I

R Code