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Do men and women experience social media differently? A two-year longitudinal study of the moderating effect of gender on the social media use – well-being relationship

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- Two large, longitudinal, and random samples of U.S adults were surveyed.
- Social media use is negatively associated with physical and mental health.
- Gender moderates the SMU -> health relationship.
- Women suffer more negative health outcomes from SMU than men.
- A bidirectional relationship between health and SMU was found.
- Respondents lower in physical and mental health use social media more.

Abstract

A vigorous debate exists among academics as to the impact of social media use (SMU) on well-being writ large. To date, research has found both positive and negative results, as well as no results, regarding the relationship between these two variables. Using a large, randomly selected sample of US adults across two annual waves of data, our findings suggest that SMU is negatively associated with physical and mental health (albeit weakly). Fixed R-squared was .047 and .049 for SMU as a predictor of physical and mental health, respectively. Currently, most research on SMU and well-being has focused on adolescents. A significant relationship between SMU and health contributes to the narrative that SMU may be associated with poorer perceptions of both physical and mental health. The study also finds that gender moderates this relationship. Women, as hypothesized, are more likely to report lower levels of physical and mental health from SMU than men. Our results also find a bidirectional relationship between SMU and health. Those reporting lower physical and/or mental health were more likely to use social media than those in better perceived health. And these results held across genders. Fixed R-squared was .097 for both mental and physical health. The study's findings have important implications for research in this area and for public policy.

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1. Introduction

The question is simple: does SMU have a positive or negative impact on well-being? The answer to this question is a bit more difficult and nuanced. However, both the question and its possible answer(s) are vitally important given the amount of time people spend on social media. Current estimates show that 73% of Americans use social media and spend an average of 2 hours and 16 minutes daily on it. To put this in perspective, the average American is spending more time on social media than they do on eating and drinking (1.18 hours per day), personal grooming (.88 hours per day), religious and spiritual activities (1.57 hours per day), and telephone calls, e-mail, and mail (1.01 hours per day) (Bureau of Labor Statistics, 2024).

Understanding the outcomes of so much time spent on social media is critical given that SMU has been shown to affect nearly all aspects of our lives including our mental (Ajewumi et al., 2024) and physical well-being (Lee et al., 2022), our relationships (Roberts & David, 2016) and performance at work (Roberts & David, 2020) or school (Kus, 2025). Ironically, as time spent on social media has increased, so has loneliness (Roberts, Young, & David, 2024). According to the recent US Surgeon General's Report (2023), the average amount of time spent alone increased from 142.5 hours per month in 2003 to 166.5 hours per month in 2020 - an increase of nearly 17% or 24 additional hours spent alone each month. In the same period, the time spent in person with friends dropped from 60 minutes per day (30 hours per month) to 20 minutes per day (10 hours per month). One could argue that the time lost in face-to-face interactions was made up for by time spent on social media. The question then remains, how has this dramatic shift in how Americans spend their time affected their mental and physical health?

Study Contributions

The present study makes several important contributions to this evolving area of research. First, it examines the relationship between social media use (SMU) and both mental and physical health, contributing to a more comprehensive understanding of well-being outcomes.

Second, the study leverages a large, randomly selected sample of U.S. adults (n = 18,224), enhancing the generalizability of the findings. In addition, the use of two years of longitudinal data addresses a critical limitation in existing literature, which has been predominantly cross-sectional (Parry et al., 2022). This design responds to repeated calls for more longitudinal research to better assess temporal relationships (Parry et al., 2022; David et al., 2017; Valkenburg, 2022).

Third, the study examines gender as a moderator of the relationship between SMU and well-being. Despite evidence that SMU outcomes may differ by gender, with women often experiencing more negative effects (Twenge & Farley, 2021; Twenge et al., 2022), this factor remains underexplored in prior research. Finally, the study investigates the potential bidirectional relationship between SMU and well-being. While prior work suggests that individuals experiencing anxiety, stress, or depression may turn to social media as a coping mechanism, this possibility has received limited empirical attention (O'Day & Heimberg, 2021; Roberts, Young, & David, 2024; Shrum et al., 2022).

SMU and Well-Being

It might be best to summarize the extensive literature on the relationship between SMU and well-being as an "embarrassment of riches." Despite the volume of published research on the subject, vigorous debate persists, and findings are often inconsistent regarding SMU's impact on and relationship with well-being (Valkenburg et al., 2022). In fact, Valkenburg (2022) conducted a scoping review of 27 reviews (nine meta-analyses, nine systematic reviews, and nine narrative reviews) and concluded that many of the reviews produced inconsistent results regarding SMU and measures of well-being and ill-being. In summarizing six meta-analyses whose focus was the SMU-well-being relationship, Valkenburg et al. (2022) conclude "social media use does not have an unambiguously good or bad impact on well-being, but rather that associations are inherently complex and nuanced …" (p.3). Based on her umbrella review of 27 reviews of the SMU-well-being relationship, Valkenburg (2022) concludes that meta-analyses of the literature that aggregate between-person effects and measure SMU in terms of time spent on social media are no longer needed. The relationship between SMU and well-being is more complex and nuanced, and such aggregated results may distort, or even over- or under-report the relationships studied. Pouwels et al. (2021) argue that SMU may have both positive and negative effects, or even cumulative effects, in which short-term SMU effects compound over time to produce long-term negative effects.

Given concerns about aggregating study results through meta-analyses, reviews, and scoping reviews, we will next address several seminal studies that, frustratingly, have found positive, negative, both positive and negative, and no relationships between SMU and well-being in its many forms. Research by Twenge and colleagues (Twenge & Farley, 2021; Twenge, Haidt, Lozano, and Cummins, 2022; Twenge & Campbell, 2019) has found a relatively consistent negative relationship between SMU and well-being.

Twenge et al. (2020) questioned the results of Orben and Przybylski's (2019) research, which used an advanced statistical technique called Specification Curve Analysis. Across three large datasets, the researchers found a very small negative correlation between SMU and well-being (0.4 percent). Orben and Przybylski stated this relationship was "too small to warrant policy change" (p. 173). Twenge et al. (2020) argued that Orben and Przybylski's (2019) Specification Curve Analysis underestimated the harm caused by digital media consumption. Twenge et al. (2020) focused on six analytical decisions they believed contributed to the lower effect size observed between SMU and well-being. The researchers argue that these results are in stark contrast to other research conducted with the same datasets. Using the Millennium Cohort Study dataset, one of the data sets used by Orben and Przybylski (2019), Kelly et al. (2018) found that heavy users of social media exhibited levels of depression that were twice as high as non-users.

Twenge et al. (2020) point out that Orben and Przybylski's (2019) results may have been a function of only considering monotonic effects of SMU on well-being. This, despite Przybylski, who stated in an earlier paper that associations between SMU and well-being are likely to follow a J-shaped curve, a pattern that Przybylski and Weinstein (2017) labeled the Goldilocks hypothesis. Other concerns raised by Twenge et al. (2020) included the aggregation of data across screen types and genders. It is noted that girls are affected more strongly and negatively than boys. Twenge et al. also note that Orben and Przybylski (2019) relied upon single-item scales, did not use certain measures that would have provided more variance, used controls that may have been better utilized as mediators, and used R-squared as an effect size. Twenge et al. (2020) argue that r-square may not be a useful indicator of effect size because it yields small values (e.g., r = .15 and r-square = 2.3%). Twenge et al. (2020) also questioned why Orben and Przybylski (2019) chose the variables they did (e.g., wearing glasses, eating potatoes) to compare the relative importance of SMU for well-being. Twenge et al. (2022) later reran analyses on the same three datasets that Orben and Przybylski (2019) had previously used. To facilitate comparisons with Orben and Przybylski's (2019) results, the researchers also used Specification Curve Analysis (SCA). However, Twenge et al. (2022) applied different "analytical constraints" to the same three datasets. They examined digital media activities separately (e.g., social media use alone), separated respondents by gender, excluded potential mediators from the controls, and treated scales equally to prevent a multi-dimensional scale from having an outsized effect on outcomes. The revised analysis found several stronger relationships than those in the original analysis by Orben and Przybylski (2019). In particular, the researchers found a "substantial" association between girls' mental health and social media use, with Betas ranging from -0.11 to -0.24. The authors conclude that these associations were stronger than the relationships found between mental health and other serious behaviors, including binge drinking, obesity, drug use, and sexual assault, suggesting SMU is an important public policy concern.

Using the same three data sets, Twenge and Campbell (2019) found that light users of digital media (1< hour per day) reported higher levels of psychological well-being than heavy users (5+ hours per day). Heavy users of digital media were also found to be more likely to be unhappy, low in well-being, more depressed, and suffering from more suicidal ideation or past suicide attempts than light users. Heavy users were twice as likely to have attempted suicide. The researchers note that their results support the Exposure-Response Model regarding the impact of digital media use on well-being. The higher the level of digital media use, the worse respondents reported feeling.

These results are in stark contrast to those of Przybylski and Weinstein (2017), who analyzed a large sample of 15-year-olds in the UK. Their research found that high levels of SMU accounted for less than 1% of the variability in respondent well-being. In strongly worded comments based on the results of their research, Przybylski and Weinstein (2017) argue that the importance attributed to SMU's impact on well-being by other researchers may not have the practical implications they purport. Later, Przybylski stated that previous research results reached only the barest minimum standards of quality, "that people wouldn't laugh you out of the room" (Twenge & Campbell, 2019, p. 312). Clearly, a chasm exists between these two groups of researchers regarding the impact of SMU on well-being, highlighting the importance of data quality, analytical constraints, and research methods.

Recent research by Vuorre and Przybylski (2023a, 2023b, 2024) has also drawn critical attention from fellow researchers. Generally, Vuorre and Przybylski, across these three studies, found that Facebook adoption

and internet access were associated with small positive or inconsistent effects on mental health. Sigaud et al. (2025) argue that Vuorre and Przybylski's research suffers from several issues that "reduce their relevance to questions about social media's effect on adolescent mental health" (p. 2). The major criticisms leveled by Sigaud et al. (2025) include the inappropriate combining of years, countries, ages, and measures, Facebook's involvement in the research design of one study, problems related to the use of two of the international data sets, and the inability to make causal inferences between their independent and dependent variables.

Przybylski and Vuorre (2025) offered their rebuttal to the above concerns. They fashioned a rigorous and credible response to each of Sigaud et al.'s concerns. Przybylski and Vuorre (2025) argue that "precision matters when using terminology, conducting analysis, sourcing diverse data, and interpreting causal claims" (p. 9). Scientific rigor, they argue, is the path forward, acknowledging that all research has its own limitations. Although they reach different conclusions about the proper analysis of the data in question, both groups appear to agree that this is an important topic, and the approach used to analyze the data has substantial implications for the results it generates. To complicate matters further, a recent summary (not statistically aggregated across meta-analyses) by Ajewumi et al. (2024) of the SMU-well-being literature found that SMU can have both positive and negative effects on mental health. The researchers conclude that SMU can facilitate social connection and community building and help maintain relationships. SMU can also serve as a creative outlet and voice, allowing users to build an identity, advocate for social causes, and access mental health resources and supportive communities.

On the other hand, the researchers argue that SMU can also have a negative impact on mental health, and this negative influence appears to be growing. Social comparison is rampant on social media and can lead to lower self-esteem and feelings of inadequacy, the authors argued. Anxiety, stress, and depression are common outcomes of high or problematic social media use (Crumly-Goodwin et al., 2025; Hussain & Griffiths, 2021). FoMO has long been identified as a possible negative outcome of SMU (Przybylski et al., 2013). Lastly, excessive use and reliance on SMU can lead to addiction (Griffiths & Kuss, 2017). An over-reliance/addiction on SMU can negatively impact all aspects of an individual's life, including how they feel about themselves, their relationships, and their physical and mental well-being (David, Roberts, and Christenson, 2017).

A recent meta-analysis of the SMU-well-being relationship by Ansari et al. (2024) highlights the difficulty in determining the relationship between SMU and well-being. In their meta-analysis of 51 studies, Ansari et al. (2024) focused on the potentially positive outcomes of SMU (subjective and psychological well-being). Study results found that, across a combined sample of 680,506 individuals, excessive SMU was not associated with subjective well-being. Although research evidence has found SMU can have a positive impact on well-being in its many forms (e.g., Beyens et al., 2020; Huang, 2021; Oliver, 2022), a large body of extant research on SMU and well-being has found it to be negatively associated with well-being. SMU has been found to be associated with heightened anxiety, stress, depression, loneliness, and lower self-esteem, life satisfaction, subjective well-being, and sleep quality (Abi-Jaoude, et al., 2020; Adams & Kisler, 2013; Ahmed et al., 2024; Ajewumi et al., 2024; Keles et al., 2020; Kross et al., 2013; Liu et al., 2019; Lopes et al., 2022; Primack et al., 2017; 2021; Roberts, Young, & David, 2024; Tromholt, 2016; Twenge, 2019; Twenge, Spitzberg, & Campbell, 2019; Vidal et al., 2020; Valkenburg, 2022; Verduyn et al., 2017; Wang et al., 2018; Woods & Scott, 2016). Schonning et al. (2020), based on their scoping review of the SMU literature, warn that the preponderance of negative associations between SMU and well-being may be due to most studies focusing on its potentially negative outcomes. The study presented herein, however, looks at both positive and negative health-related outcomes of social media use. Given the above, we offer our first hypothesis:

H1: SMU will be negatively associated with physical and mental health.

The Moderating Effect of Gender

The moderating role of gender in the relationship between SMU and well-being is important but often overlooked. Too often, gender is used as a control variable, thereby precluding a deeper understanding of its relationship with SMU outcomes (Twenge & Martin, 2020; Twenge & Farley, 2021). Research by Svensson, Johnson, and Olsson (2022) used survey data from a sample of 3957 Swedish adolescents and found that social media use impacted well-being only for girls. Girls posting information about themselves on social media, argue the authors, are particularly vulnerable to lower levels of reported well-being.

Women, more than men, use social media to maintain relationships, socialize, express themselves, and share photos (McAndrew & Jeong, 2012; Muscanell & Guadagno, 2012; Tifferet, 2020; Twenge & Martin, 2020). Women also spend more time on social media than men (Theophilou et al., 2024; Twenge & Martin, 2020). These proclivities make them more susceptible to the content they encounter on social media (Gentzler et al.,

2023; Shensa et al., 2018). Women often face greater scrutiny about how they look, their friend groups, and their behavior on social media. Men are more oriented toward online entertainment, gaming, and information, and are focused on projecting an image of strength and success (Ajewumi et al., 2024).

Twenge and Farley (2021) used a secondary data set of 13- to 15-year-old adolescents from the UK. The researchers asked respondents how much time they spend daily on social networking, messaging, or other internet sites or apps, including Facebook, Twitter, and WhatsApp. Although not an optimal measure of social media use (it includes messaging apps and is self-reported), the researchers analyzed whether such use was related to self-harm behaviors, depressive symptoms, self-esteem, and life satisfaction. Results found that daily hours spent on social media were more strongly associated with self-harm behaviors, depressive symptoms, and low self-esteem and life satisfaction than other forms of screen activities, including watching TV and electronic gaming. And, importantly, girls showed stronger negative associations between screen time and media activities and their well-being than boys did. Heavy internet users among girls were 166% more likely to exhibit symptoms of depression than girls who use the internet less. Boys exhibited the same relationship between internet use and depression as girls, but not as strongly. Heavy users among boys were 75% more likely to exhibit depressive symptoms than lower-use boys. The authors conclude that social media and internet use among girls are the most strongly associated with lower mental well-being. Using three large datasets used by both Orbin and Przybylski (2019) and Twenge et al. (2022), Twenge and Martin (2020) sparked a lively academic debate about research design and analysis. Twenge and Martin (2020) found that adolescent girls spent more time on social media than boys, and the relationship between moderate or heavy digital media use and poor psychological well-being was, in most cases, larger for girls than for boys. Heavy social media users across both genders were approximately twice as likely as low users to suffer from mental health issues, experience lower well-being, and exhibit higher risk factors for self-harm. The authors conclude that "associations between heavy digital media use and low psychological well-being are larger for adolescent girls than boys" (p. 91). Given the above, we offer the following hypotheses:

H2: Gender will moderate the relationship between social media use and well-being, such that women will report lower physical, mental, and overall health than men as a result of their SMU.

Does a Bidirectional Relationship Exist Between SMU and Health?

An existing body of research has found that SMU can lead to both positive and negative outcomes (Alwuqaysi et al., 2025; Przybylski et al., 2021; Roberts & David, 2023; Valkenburg et al., 2022). However, little research has examined the possibility that the relationship between SMU and well-being may be bidirectional (O'Day & Heimberg, 2021). Shrum, Fumagalli, and Lowrey (2022) argue that lonely people navigate social media to assuage their sense of disconnection. In turn, the authors argue that heightened social media use may exacerbate their sense of loneliness. Likewise, Nowland, Necka, and Cacioppo (2018) argue that a bidirectional relationship exists between loneliness and SMU. The authors argue that how social media is used will determine whether it has a negative or positive relationship with low minus. When social media is used to bolster existing relationships and forge new ones, its impact may decrease feelings of loneliness. However, when it is used more passively to avoid social interactions, feelings of loneliness may increase.

An emerging body of research regarding the possible bidirectional relationship between SMU and well-being exists (Beyens et al., 2021; Boers et al., 2019; David & Roberts, 2023; Raudsepp & Kais, 2019; Roberts, Young, & David, 2024; Tuck & Thompson, 2025; Valkenburg et al., 2022). Recent research by Tuck and Thompson (2025) found that a bidirectional relationship exists between social media use and well-being. Using experience sampling (5 surveys per day for 2 weeks) from a sample of 179 US adults, the authors found that social media is often used for emotion regulation. Approximately 40% of SMU episodes were calculated attempts to regulate emotions. Results also found that participants were more likely to use social media when they felt depressed. Social media users, the authors assert, use social media to improve their mood, distract themselves from negative feelings, and connect socially. As a tool for regulating mood, its effectiveness can affect subsequent well-being. Tuck and Thompson (2024) created an SMU scale that distinguishes between different types of SMU. As expected, different types of SMU led to different emotional outcomes. Using a large, randomly selected sample of Dutch adults (n = 6,965) over a nine-year period, Roberts, Young, and David (2024) investigated the hypothesized impact of SMU (active and passive) on loneliness over the nine-year period. The results showed that SMU was associated with increased loneliness over the period covered. The authors also investigated a possible bidirectional relationship between the two variables. Results showed that higher levels of loneliness were associated with greater social media use. Interestingly, both active and passive SMU were found to increase reported loneliness, which, in turn, increased SMU. The authors assert that "a continuous

feedback loop exists between the two variables" (Roberts et al., 2024). Given the above, we offer our third hypothesis:

H3: A bidirectional relationship exists between SMU and physical and mental well-being, such that lower levels of perceived physical and mental health will predict higher levels of subsequent social media use.

2. Method

Transparency and Openness

The data used in this study are secondary, derived from the Population Assessment of Tobacco and Health (PATH) Study, and are available here:

https://www.icpsr.umich.edu/web/NAHDAP/studies/37519/datadocumentation.

All data with the PATH panel are de-identified, and the dataset is publicly available, thus exempting it from institutional review board (IRB) approval. A comprehensive list of publications that have used the PATH data is available at https://www.icpsr.umich.edu/web/NAHDAP/studies/37519/publications. To the best of our knowledge, no prior research has specifically examined the longitudinal effects of social media use using these data. All analysis code, output files, and supplementary materials are publicly accessible on the authors' OSF page.

Sample

The data for this study are drawn from the PATH panel, a large, nationally representative sample of US households. The PATH panel includes annual waves of data collected from 2013 to 2022. Our analyses focus on the two most recent waves, as earlier waves do not include the SMU measure central to our research. As such, our analysis begins with Wave 6 (2021) and extends through Wave 7 (2022), the most recent available wave.

Across both waves of data, 18,224 participants (57.7% female) provided 36,448 assessments of health and SMU. As the dataset consisted of two waves, all individuals in the final dataset were included in both waves, because including individuals only once would prevent the longitudinal model from converging. Table 1 shows the descriptive statistics of the sample in each wave.

Table 1. Descriptive statistics for the sample.

Wave	Age category	Gender	N	Ave. Physical Health (SD)	Ave. Mental Health (SD)	Ave. SMU (SD)
1	18—24	Male	2856	3.92 (0.93)	3.54 (1.10)	4.13 (1.59)
		Female	3421	3.77 (0.93)	3.11 (1.11)	4.51 (1.57)
	25—34	Male	2112	3.75 (0.92)	3.55 (1.03)	3.81 (1.51)
		Female	2936	3.62 (0.95)	3.21 (1.06)	4.11 (1.52)
	35—44	Male	926	3.55 (0.94)	3.58 (0.99)	3.46 (1.36)
		Female	1384	3.5 (0.96)	3.33 (1.02)	3.65 (1.43)
	45—54	Male	723	3.42 (0.99)	3.54 (1.01)	3.29 (1.33)
		Female	1064	3.32 (1.01)	3.31 (1.08)	3.47 (1.45)
	55—64	Male	603	3.39 (0.99)	3.66 (0.98)	3.16 (1.29)
		Female	968	3.3 (1.00)	3.38 (1.04)	3.36 (1.37)
	65 or more	Male	490	3.36 (0.98)	3.84 (0.92)	3.05 (1.28)
		Female	742	3.44 (0.94)	3.68 (0.95)	3.22 (1.29)
2	18—24	Male	2856	3.86 (0.97)	3.49 (1.16)	4.26 (1.64)
		Female	3421	3.67 (0.96)	3.06 (1.16)	4.54 (1.59)
	25—34	Male	2112	3.74 (0.96)	3.54 (1.09)	3.87 (1.49)
		Female	2936	3.56 (0.97)	3.23 (1.11)	4.14 (1.51)
	35—44	Male	926	3.57 (0.95)	3.59 (1.04)	3.50 (1.32)
		Female	1384	3.52 (0.96)	3.34 (1.07)	3.67 (1.41)
	45—54	Male	723	3.46 (0.96)	3.51 (1.03)	3.41 (1.39)
		Female	1064	3.35 (1.01)	3.34 (1.08)	3.54 (1.43)
	55—64	Male	603	3.4 (0.99)	3.67 (1.00)	3.25 (1.25)
		Female	968	3.37 (1.02)	3.41 (1.05)	3.34 (1.32)
	65 or more	Male	490	3.36 (0.98)	3.77 (1.02)	3.11 (1.23)
		Female	742	3.44 (0.95)	3.69 (0.97)	3.13 (1.24)

Before constructing the models presented in this study, all quantitative variables were centered using grand-mean centering (Stavrova & Ren, 2021). Variance inflation factors (VIFs) for the explanatory variables in our analyses were all below 1.5, indicating that multicollinearity did not pose a concern in our models.

Measures

The measures used in the current study were dictated by the availability of data in the large, nationally representative PATH study described above. Health was measured using self-reported perceptions of "physical health" and "mental health," the latter of which included stress, depression, and problems with emotions. Each item was rated on a 5-point scale ranging from 1 (Excellent) to 5 (Poor). Both items were reverse-scored so that higher values indicate better health.

Social media use was assessed using two items: (1) *hours spent on social media on an average weekday* and (2) *hours spent on social media on an average weekend day*. For the weekday measure, participants indicated their typical daily use on an 8-point scale (1 = none, 2 = less than an hour, 3 = 1–2 hours, 4 = 3–4 hours, 5 = 5–6 hours, 6 = 7–8 hours, 7 = 9–10 hours, and 8 = 11 hours or more). For the weekend measure, participants responded using a 9-point scale (1 = none, 2 = half hour or less, 3 = about an hour, 4 = about 2 hours, 5 = about 3 hours, 6 = about 4 hours, 7 = about 5 hours, 8 = about 6 hours, and 9 = 7 hours or more). Because the two items were measured on non-equivalent ordinal scales with different categorical structures and upper bounds, they were placed on a common metric prior to aggregation. Specifically, each item was standardized (i.e., z-score) across the sample, yielding variables with a mean of zero and a standard deviation of one. Standardization removed differences in scale units and dispersion, ensuring that each indicator contributed equally to the composite measure despite its different response formats. The standardized weekday and weekend scores were then averaged to create a single index of overall social media use (SMU). This approach preserved the ordinal information contained in the original responses while producing a continuous variable that reflects individuals' relative standing in overall social media engagement across the week.

Model Specifications

Linear mixed-effects models were employed to analyze the data, as they are well-suited for modeling change over time and are widely regarded as the optimal statistical method for analyzing longitudinal data (Cunnings, 2012; Gries, 2015; Lei et al., 2023; Linck & Cunnings, 2015). Our methodological approach aligns closely with those adopted in prior studies (Decker et al., 2023; Lei et al., 2023; Nestler & Humberg, 2024; Roberts, Young, & David, 2024; Saragosa-Harris et al., 2022), reflecting a consistent framework for handling longitudinal data. Mixed-effects models are advantageous because they can incorporate random effects to account for individual variability and unobserved heterogeneity in longitudinal trajectories. These models estimate both fixed effects (i.e., population-level parameters) and random effects (i.e., subject-specific deviations), providing a robust framework for controlling multiple levels of the data. Importantly, random effects facilitate the estimation of individual-specific intercepts and slopes, capturing variations in baseline levels and rates of change among participants. All statistical models were implemented in R version 4.2.3 using the nlme package (R Core Team 2020). Significance testing for fixed effects was performed using the lmerTest package (Kuznetsova et al., 2017; Lei et al., 2023). While previous researchers have used the widely recognized R package lme4 to construct mixed-effects models (e.g., Bates et al. 2015; Decker et al., 2023), we opted to use the nlme package because it provides straightforward handling of random-effects covariance structures and allows a more tailored fit to our data. We assessed the performance of each covariance structure by comparing Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores. As reported in Tables 1 and 3 (main models) and 5 and 7 (bidirectional models) on the OSF page, the diagonal covariance structure provided the best overall fit across all considered model specifications, consistently yielding the lowest AIC and BIC values. In addition, we incorporated an autoregressive structure of order 1 (i.e., AR(1)) to model correlations between repeated measures within individuals, assuming that the correlation decreases exponentially with increasing time interval between measurements. Finally, several covariance structures for the random effects were considered, including the identity, diagonal, symmetric, and compound symmetry covariance matrices.

3. Results

In our analysis of physical health over time, age, gender, wave, SMU, and the interaction between gender and SMU were included as predictor variables. The residual diagnostics for this model, including histograms of

the residuals and a residual plot of the standardized residuals, are shown in Figures 1 and 2 on our OSF page. Results of this model yielded the equation presented below, which is henceforth referred to as equation (1):

Physical Health = 3.683 – 0.114*AGE – 0.110*GENDER – 0.025*WAVE – 0.070*SMU – 0.042*GENDER*SMU

The fixed effects coefficients, reported in Table 2, indicate that, after controlling for other variables, women reported significantly lower physical health than men (β = -0.110, p < .001). Age was negatively associated with physical health (β = -0.114, p < .0001), consistent with declining health across age groups. Wave was also negatively associated with physical health (β = -0.025, p < 0.001), suggesting a small but significant decline in reported physical health over time in the sample. Social media use was a significant predictor of physical health, such that greater SMU was associated with lower physical health (β = -0.070, p < .0001). Moreover, the interaction between gender and SMU was significant (β = -0.042, p < .0001), indicating that the negative association between SMU and physical health was stronger among women than men.

Table 2. Results for the model test where physical health is the response variable.

Fixed effect	Estimate	Std. Error	DF	t-value	p-value
Intercept	3.682975	0.009847989	18222	373.9824	<0.0001
gender	-0.109650	0.012968327	18222	-8.4552	<0.0001
age	-0.114102	0.004168887	18220	-27.3698	<0.0001
wave	-0.024803	0.006013275	18220	-4.1248	<0.0001
SMU	-0.069643	0.007699626	18220	-9.0449	<0.0001
gender*SMU	-0.041816	0.010279167	18220	-4.0680	<0.0001

Substantively, these coefficients indicate that, for males, each one-unit increase in SMU above the mean is associated with approximately a 0.070-point decrease in health on the 5-point scale, indicating slightly worse physical health. For females, a one-unit increase above the mean corresponds to approximately a 0.112-point decrease in physical health, indicating a more pronounced decline than for males on average. The output revealed notable individual-level variability in baseline physical health and rates of change over time (see Table 3). Specifically, the random-intercept standard deviation was 0.846, indicating substantial variation in initial physical health across individuals. The standard deviation of the random slope for the time variable (i.e., wave) was 0.114, reflecting individual differences in overall health trajectories. Although this slope variability was less pronounced than the intercepts, it indicates that participants exhibited different trends.

Table 3. Model results: Physical health is the dependent variable.

	pdDiag
AIC	90521.49
BIC	90615.03
Estimates	
Intercept	3.682975
Gender	-0.109650
Age	-0.114102
Wave	-0.024803
SMU	-0.069643
Gender*SMU	-0.041816
Standard deviation for Random effects	
Intercept	0.8455287
Slope	0.1142251
Residual	0.387671
AR 1 correlation	-0.99118
R^2	
Random effects	0.795521
Fixed Effects	0.04655269
Overall	0.8420736

The AR(1) correlation structure indicated strong autocorrelation in the residuals (fi = 0.99), capturing dependence within repeated measures only after accounting for random intercepts and slopes. To evaluate model efficacy, we utilized the R^2 metric, specifically calculated through the rsq package in R (Zhang, 2022),

which provides estimates of variance explained by fixed effects, random effects, and the full model in mixed-effects frameworks. The fixed effects accounted for approximately 4.66% of the total variance in physical health ($R^2 = 0.047$), indicating a modest contribution of the predictors included in the model. The random effects accounted for approximately 79.6% of the variance ($R^2 = 0.796$). Taken together, the model explained 84.2% of the variance in physical health (overall $R^2 = 0.842$). These findings suggest that although the fixed predictors – including SMU – have statistically reliable associations with physical health, most of the variability in physical health reflects stable between-person differences captured by the random effects.

Results: Mental Health

Next, we examined SMU as the focal predictor of mental health over time, with age, gender, wave, and the interaction between gender and age included as potential predictors. The results yielded the model presented below, which we refer to as equation (2):

Mental Health = 3.562 – 0.054*AGE – 0.307*GENDER – 0.011*WAVE – 0.089*SMU – 0.046*GENDER*SMU

The fixed-effects coefficients indicate that, after controlling for other variables, women reported, on average, significantly lower mental health than men (başlat denklem beta = -0.307, p < .001). Age was positively associated with mental health (β = 0.054, p < .001), suggesting modest improvements in reported average mental health with increasing age. Wave was not significantly associated with mental health (β = -0.011, p = 0.128), indicating no reliable overall change in mental health across measurements within the sample. Social media use was a significant predictor of mental health, with greater SMU associated with lower reported mental health (β = -0.089, p < .001). In addition, the interaction between gender and SMU was statistically significant (β = -0.046, p < .001), indicating that the negative association between SMU and mental health was stronger among women than men.

Table 4. Results for model (2), where mental health is the response variable, and gender, age, wave, SMU, and the interaction term between gender and SMU are all explanatory variables.

Fixed effect	Estimate	Std. Error	DF	t-value	p-value
Intercept	3.561819	0.010826450	18222	328.9923	<0.0001
gender	-0.307266	0.014282419	18222	-21.5136	<0.0001
age	0.053649	0.004602617	18222	11.6563	<0.0001
wave	-0.010936	0.007179095	18222	-1.5234	0.1277
SMU	-0.088927	0.008934526	18222	-9.9532	<0.0001
gender*SMU	-0.046197	0.011832280	18222	-3.9043	0.0001

The findings indicate that increases in SMU are associated with steeper declines in both physical and mental health among women compared with men, on average. This result suggests that females experience disproportionately greater adverse health impacts as SMU rises over time.

Table 5. Results for model in (2), where mental health is the response variable and age, gender, wave, social media use, and the interaction term between gender and social media use are all explanatory variables.

	pdDiag
AIC	100498.4
BIC	100592
Estimates	
Intercept	3.561819*
Gender	-0.307266*
Age	0.053649*
Wave	-0.010936*
SMU	-0.088927*
Gender*SMU	-0.046197*
Standard deviation for Random effects	
Intercept	0.8417775
Slope	0.1781401
Residual	0.5806071
AR 1 correlation	-0.2876843
R^2	
Random effects	0.6683707
Fixed Effects	0.04945215
Overall	0.7178229
* indicates p-value is < 0.05.	

Additional model results, shown in Table 5, also revealed substantial individual-level variability in baseline mental health and in trajectories over time. Specifically, the standard deviation for the random intercept was 0.842, indicating considerable variation in initial mental health across individuals. The standard deviation of the random slope for time (i.e., wave) was 0.178, indicating meaningful heterogeneity in individual mental health trajectories across waves. The random effects structure, therefore, indicated meaningful variability in both baseline mental health (SD = 0.84) and rates of change across individuals (SD = 0.18), with a residual standard deviation of 0.581. The AR(1) correlation structure indicated a moderate negative autocorrelation in the residuals (phi =- 0.288), capturing dependence among repeated measurements within individuals after accounting for random intercepts and slopes. The model's fixed effects accounted for approximately 4.95% of the total variance in mental health ($R^2 = 0.049$), suggesting a modest contribution of the predictors included in the model. The random effects accounted for approximately 66.8% of the variance (R^2=0.668). Taken together, the model explained 71.8% of the variance in mental health ($R^2 = 0.718$).

Bidirectional Models

To examine the possibility of reciprocal associations between SMU and both physical and mental health, we next estimated bidirectional models in which SMU was specified as the response variable and physical and mental health as the focus predictors. By reversing the roles of the variables, the present analysis evaluates whether physical and mental health independently predict subsequent SMU levels, thereby providing a more comprehensive assessment of their dynamic relationship.

Physical Health

In our bidirectional approach, we first assessed the extent to which physical health predicts subsequent SMU. The results yielded the model presented below, which is henceforth referred to as equation (3):

SMU = 3.774 + 0.226*GENDER – 0.287*AGE + 0.045*WAVE – 0.153*Physical Health – 0.015*GENDER*Physical Health

The fixed-effects coefficients indicate that, after controlling for other variables, women reported significantly higher SMU than men (β = 0.226, p < .001). Age was negatively associated with SMU (β = -0.287, p < .001), indicating lower levels of SMU among older participants. Wave was positively associated with SMU (β = 0.045, p < .001), suggesting an increase in SMU over time. Physical health emerged as a significant predictor of SMU, with better physical health associated with lower SMU (β =-0.153, p < .001). However, the interaction between gender and physical health was not statistically significant (β = -0.015, p = 0.364), indicating that the association between physical health and SMU did not differ between men and women. The overall model summary is presented in Table 6.

Table 6. Results for bidirectional model (3), where SMU is the response variable, and gender, age, wave, physical health, and the interaction term between gender and physical health are all explanatory variables.

Fixed effect	Estimate	Std. Error	DF	t-value	p-value
Intercept	3.773685	0.014772744	18222	255.44915	<0.0001
gender	0.225793	0.019444593	18222	11.61212	<0.0001
age	-0.286618	0.006167756	18222	-46.47040	<0.0001
wave	0.044721	0.010446752	18222	4.28085	<0.0001
physical health	-0.152758	0.012791130	18222	-11.94247	<0.0001
gender*physical health	-0.014977	0.016479852	18222	-0.90880	0.3635

Additional model results, shown in Table 7, also revealed substantial individual-level variability in baseline SMU but negligible variability in rates of change over time. Specifically, the random-intercept standard deviation was 1.293, indicating considerable variation in initial SMU levels across individuals. In contrast, the estimated standard deviation of the random slope for time (wave) was effectively zero (SD close to 0), suggesting minimal between-person variability in SMU trajectories after accounting for fixed effects. The residual standard deviation was 0.727, indicating moderate within-person variability not explained by the model.

The random-effects structure, therefore, indicated pronounced heterogeneity in baseline SMU but little evidence that individuals differed in their rates of change across waves. The AR(1) correlation structure revealed extremely strong negative autocorrelation of residuals ($\phi = -0.999$), capturing the dependence of repeated measurements within individuals after accounting for random intercepts.

Table 7. Results for the bidirectional model (3), where SMU is the response variable and age, gender, wave, physical health, and the interaction term between gender and physical health are explanatory variables.

	pdDiag
AIC	125425.8
BIC	125519.3
Estimates	
Intercept	3.773685*
Gender	0.225793*
Age	-0.286618*
Wave	0.044721*
Physical Health	-0.152758*
Gender*Physical Health	-0.014977
Standard deviation for Random effects	
Intercept	1.293459
Slope	<0.0001
Residual	0.7267233
AR 1 correlation	-0.9994278
R^2	
Random effects	0.6842649
Fixed Effects	0.09672226
Overall	0.7809871

* indicates p-value is < 0.05.

The fixed effects accounted for approximately 9.67% of the total variance in SMU , sağ parantez, indicating a meaningful contribution of the predictors to explaining SMU). The random effects accounted for approximately 68.4% of the variance ($R^2 = 0.684$). Overall, the model explained 78.1% of the variance in SMU ($R^2 = 0.781$). These findings suggest that while physical health is a statistically significant predictor of SMU, a substantial portion of variability reflects stable between-person differences captured by the random intercept.

Mental Health

Finally, we examined whether mental health predicts SMU over time. The results yielded the model presented below, which is henceforth referred to as equation (4):

SMU = 3.787 + 0.200*GENDER – 0.259*AGE + 0.048*WAVE – 0.144*(Mental Health) – 0.028*GENDER*Mental Health

The fixed-effects coefficients indicate that, after controlling for all other considered factors, women reported significantly higher SMU than men (β = 0.200, p < .001). Age was once again negatively associated with SMU (β = -0.259, p < .001), indicating lower levels of SMU among older participants, on average. Wave was positively associated with SMU (β = 0.048, p < .001), suggesting an increase in SMU over time. Mental health was a significant predictor of SMU, with better mental health associated with lower SMU (β = -0.144, p < .001). The interaction between gender and mental health did not reach conventional levels of statistical significance (β = -0.028, p = 0.091), indicating that the association between mental health and SMU was broadly similar for men and women.

Table 8. Results for bidirectional model (4), where SMU is the response variable, and gender, age, wave, mental health, and the interaction term between gender and mental health are all explanatory variables.

Fixed effect	Estimate	Std. Error	DF	t-value	p-value
Intercept	3.787250	0.014884421	18222	254.44389	<0.0001
gender	0.199846	0.019567663	18222	10.21307	<0.0001
age	-0.259492	0.006136174	18222	-42.28882	<0.0001
wave	0.047729	0.010443847	18222	4.57006	<0.0001
mental health	-0.144397	0.012636786	18222	-11.42672	<0.0001
gender*mental health	-0.027575	0.016296797	18222	-1.69206	0.0907

Because the interaction term was not statistically significant, the main effect of mental health can be interpreted as a common effect across genders. Substantively, these results indicate that a one-standard-

deviation increase in mental health is associated with a decrease of approximately 0.144 units in SMU, holding other variables constant. Thus, individuals reporting better psychological functioning tended to engage less in social media, on average. Considered alongside the model in (2), which demonstrated that greater SMU predicts poorer mental health, on average, this pattern is consistent with a reciprocal association in which lower mental health is linked to increased social media engagement.

Table 9. Results for bidirectional model (4), where SMU is the response variable and age, gender, wave, mental health, and the interaction term between gender and mental health are all explanatory variables

	pdDiag
AIC	125413.2
BIC	125506.8
Estimates	
Intercept	3.787250*
Gender	0.199846*
Age	-0.259492*
Wave	0.047729*
Mental Health	-0.144397*
Gender*Mental Health	-0.027575
Standard deviation for Random effects	
Intercept	1.293166
Slope	<0.0001
Residual	0.7263057
AR 1 correlation	-0.9997969
R^2	
Random effects	0.6841062
Fixed Effects	0.09712306
Overall	0.7812292

* indicates p-value is < 0.05.

The random-effects estimates, shown in Table 9, revealed substantial individual differences in baseline SMU but negligible variability in trajectories over time. Specifically, the standard deviation for the random intercept was 1.293, indicating pronounced heterogeneity in initial SMU levels across individuals. In contrast, the estimated standard deviation for the random slope associated with time (wave) was effectively zero (SD $\approx$ 0), suggesting minimal between-person differences in rates of change after accounting for fixed effects. The residual standard deviation was 0.726, reflecting moderate within-person variability not explained by the model. The random-effects structure, therefore, indicates that variation in SMU is driven primarily by stable between-person differences rather than by differing temporal trajectories. The AR(1) correlation structure revealed extremely strong negative autocorrelation of residuals ($\phi = -0.9998$), capturing the dependence of repeated measurements within individuals after accounting for random intercepts.

The fixed effects accounted for approximately 9.71% of the total variance in SMU ($R^2 = 0.097$), indicating a modest but nontrivial contribution of the predictors. The random effects accounted for approximately 68.4% of the variance ($R^2 = 0.684$). Overall, the model explained 78.1% of the variance in SMU ($R^2 = 0.781$). These findings suggest that while mental health is a statistically significant predictor of SMU, a substantial portion of variability reflects stable between-person differences captured by the random intercept.

Interpretation of Results

The findings indicate a robust negative association between SMU and self-reported physical and mental health. Higher levels of SMU were associated with poorer physical health over time, on average, and this pattern extended to mental health as well. Importantly, these associations were moderated by gender in the primary outcome models: women not only reported lower baseline physical and mental health than men, but the adverse effects of SMU were more pronounced among women. Thus, increases in SMU were linked to steeper declines in both physical and psychological well-being for women, suggesting that social media engagement may amplify existing gender disparities in health outcomes. Health also declined modestly over time in the sample, and this decline was greatest among women who reported higher SMU, indicating a compounding interaction between gender, behavior, and longitudinal health trajectories.

Bidirectional analyses provided additional insight into the nature of this relationship. When physical and mental health were modeled as predictors of SMU, better health in both domains was associated with lower SMU. In other words, individuals reporting poorer physical or mental health tended to engage more heavily in SMU. Notably, however, these reverse associations did not differ significantly by gender, indicating that the tendency for poorer health to coincide with greater SMU operates similarly for men and women. This asymmetry – gender differences in SMU predicting health, but not in health predicting SMU – suggests that women may be more vulnerable to the negative consequences of social media exposure, even though both genders appear similarly likely to increase usage when experiencing poorer health. Taken together, the results are consistent with a potentially reciprocal relationship in which higher SMU is associated with worsening health, and poorer health is associated with greater SMU engagement. However, the gender-specific vulnerability observed only in the SMU-to-health direction implies that social media may function less as a neutral coping outlet and more as a differential risk factor, particularly for women. This pattern is consistent with theoretical accounts that emphasize gender differences in online experiences, such as greater exposure to appearance-related content, social comparison pressures, harassment, or emotional labor in digital spaces.

From a policy perspective, these findings underscore the importance of moving beyond uniform recommendations regarding SMU. Public health guidelines, digital literacy initiatives, and platform design policies may need to account for gender-specific risk profiles, particularly for mental and physical well-being outcomes. Interventions aimed at reducing the harmful effects of SMU – such as promoting healthier online behavior, improving content moderation, or encouraging the use of time-management tools – may be especially beneficial for women, who appear disproportionately affected by higher levels of engagement. At the same time, bidirectional evidence suggests that elevated SMU may also indicate underlying health vulnerabilities in both men and women. Consequently, clinicians, educators, and policymakers might consider high SMU not only a potential risk factor but also a behavioral signal that individuals may benefit from supportive health interventions.

4. Discussion

The goal of the present research was to investigate the impact of SMU on the physical and mental health of US adults. We were also interested in whether gender moderated this relationship. We studied these relationships across two annual waves of data collected from a large, random sample of US adults. There has been a spirited debate concerning SMU's relationship with well-being across its many forms (Sigaud et al., 2025; Przybylski & Vuorre, 2025). The present study makes several notable contributions to the extant literature in this important area of research. An extensive body of research has found that SMU contributes to heightened levels of stress, anxiety, depression, and even suicidal thoughts and behavior (e.g., Twenge, Haidt, Lozano, and Cummins, 2022). However, extant research has also found a small, positive, or no association with a variety of well-being outcomes (Orben & Przybylski, 2019). The present research, with its significant findings regarding the relationship between SMU and health, contributes to the narrative that SMU may be associated with poorer perceptions of physical and mental health.

Given the temporal stability of health ($r = 0.691$) across waves, the amount of variance available to be explained by time-varying predictors is inherently limited. The relatively small effect sizes found in this study were not surprising, and the results offer useful insights that could inform public health policies or individual interventions. From a broader perspective, many factors beyond SMU likely influence health and vice versa. Relatedly, the long interval between annual assessments may have diluted the observed effects. For example, participants may have experienced significant life events that affected their physical or mental health more so than changes in their screen time from months earlier (de la Rosa Fernández-Pacheco et al., 2026). It is also possible that the effects between health and SMU accumulate over time (i.e., over the span of people's lives), such that even small effects could build gradually, accumulating into meaningful changes over time (Celik et al., 2025; Funder & Ozer, 2019; Krauss & Orth, 2022; Nagata et al., 2023).

Finally, it is important to recognize that previous research suggests that effect sizes tend to be smaller when media use is self-reported rather than directly measured (Araujo et al., 2017; de la Rosa Fernández-Pacheco et al., 2026; Jones-Jang et al., 2020; Junco, 2013; Parry et al., 2021; Rozgonjuk et al., 2018; Scharkow, 2016). Despite a tendency to underestimate correlations from self-reported measures, surveys remain the most widely used method for studying individuals' media activity in inferential research. Moreover, these self-reports typically align with, and yield conclusions similar to, those derived from analyses of logged or objectively assessed data (Jones-Jang et al., 2020).

A second contribution of the present research is that we investigated gender as a moderator of the relationship between SMU and health. We found that females were more negatively impacted by SMU than males. This is an important contribution, as most previous studies have controlled for gender (Twenge & Martin, 2020; Twenge & Farley, 2021) or examined its effects only among adolescents (Orben & Przybylski, 2019; Twenge et al., 2022; Twenge & Farley, 2021).

Given the nature of adolescence, studying the role of gender in the SMU-health relationship among a large sample of US adults is an important contribution. Surprisingly, gender played the same moderating role in adults as in studies of adolescents (e.g., Twenge et al., 2022). Age was controlled for in the present analysis to remove its influence on the study results. Another contribution of the present research is that it investigated the possibility of a bidirectional relationship between SMU and health (Results are provided in Tables 6 and 8 and Figures 5–8 on the OSF page). Results suggest that those lower in physical and or mental health may be drawn to SMU to address such feelings, or distract themselves, from their negative feelings and poor physical well-being. These results are consistent with the findings of Tuck and Thompson (2025), who found that those who felt bad or were depressed use social media more as a tool to regulate their emotions. Aubry et al. (2024) also found a bidirectional relationship between upward social comparisons on Instagram and depressive symptoms. The authors state that a "vicious circle" exists between depressive symptoms and social comparisons on Instagram. From a physical health perspective, Lee et al. (2022) found SMU was positively correlated with chronic inflammation, sleep problems, and more visits to healthcare providers for perceived or real illnesses. The relationship between SMU and physical and mental well-being may have become a vicious cycle where SMU reduces physical and mental health, which in turn leads to increased use of social media.

As demonstrated by extant research in this area, studying the outcomes of SMU is both complex and nuanced. Clearly, the results of a single study will not end the debate over the impact of SMU on human well-being. As suggested by Valkenburg et al. (2022), a better approach going forward may be to eschew meta-analyses and scoping reviews that seek a blanket answer on whether SMU has positive or negative effects across all its forms or is a benign behavior with little to no impact on human well-being. A better approach may be to acknowledge the complexity of such behavior and conduct carefully designed studies that contribute to a more comprehensive understanding of this ubiquitous behavior within a necessarily more limited scope. Whether good, bad, or indifferent, any such behavior that involves so much time and affects so many people merits the research scrutiny it has received to date.

Limitations and Future Research Directions

Although the present research used a large, random, and nationally representative sample of US adults collected over two annual waves, results and conclusions drawn from the data must be tempered by certain limitations. First, out of necessity, the present research averaged two single-item measures of SMU (weekday and weekend use) to create its measure of SMU, although recent research suggests that single-item measures can be valid measures of the variable(s) under investigation and are often as reliable and valid as multi-item measures of the same variable(s) (Allen, Iliescu, and Greiff, 2022). We would have preferred a more objective measure of social media as demonstrated by David, Roberts, and Christenson (2017). However, collecting that type of data from a large sample would be prohibitive. Future research that uses objective measures of both SMU and the physical and mental health outcomes examined in this study would be a welcome addition to the literature.

A second possible limitation is the present sample. Despite having a large, representative sample of US adults, can the results from this sample be generalized to populations outside the United States? Henrich, Heine, and Norenzayan (2010) argue that the US would be considered a W.E.I.R.D. (Western, Educated, industrialized, rich, and democratic) society. Not surprisingly, the authors found research results often differ across populations and that "W.E.I.R.D. Subjects are particularly unusual compared with the rest of the species - frequent outliers" (p.61).

5. Conclusion

Across two large, longitudinal and randomly selected samples of US adults, the present study finds that social media use is negatively associated with physical and mental health. Gender was found to moderate this relationship. Women were found to suffer more negative health outcomes from social media use than men. A bidirectional relationship between health and social media use was also found. Adults reporting lower levels of physical and mental health use social media more. These findings contribute to the ongoing debate about the

impact of social media use on well-being and have important implications for human flourishing and public policy.

Statement of Researchers	
Researchers' contribution rate statement:	JAR: Conceptualization, supervision, writing- original draft preparation, writing - review & editing. MED: Conceptualization, investigation, methodology, validation, writing – review and editing. PDY: Data curation, formal analysis, investigation, methodology, validation, visualization, writing – review and editing.
Conflict statement:	This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
Data Availability Statement:	The data supporting this study's findings are available from the corresponding author upon reasonable request.
Funding:	This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
Ethical Considerations:	This research was approved by the authors' institutional review board as an exempt study. All data with the PATH panel are de-identified, and the dataset is publicly available, thus exempting it from institutional review board (IRB) approval

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