Received: 25 September 2023 | Accepted: 4 July 2024

DOI: 10.1002/jcpy.1437

JCP SCP SOCIETY FOR CONSUMER PSYCHOLOGY

RESEARCH REPORT

Social platform use and psychological well-being

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Funding information
John Fell OUP Research Fund; Henry Crown Institute of Business Research; Marketing Science Institute; Deutsche Forschungsgemeinschaft

Abstract
Social platforms facilitate the daily interactions of billions of people globally. Prior research generally concludes that social platforms negatively affect people's welfare. This research reopens this debate by using a robust methodology to examine the time series effects of social platform use on users' subjective well-being, psychological well-being, physical health, and financial security. We report a 6-month longitudinal study of 1029 adults. Participants' daily time using social platforms on their mobile device was unobtrusively tracked and their well-being was measured every 2 weeks. The findings suggest a small, positive effect of time spent using social platforms on both subjective well-being and psychological well-being (but no significant effects on physical health or financial security). Further, it is time spent using social platforms that facilitate interactions with intimate/close ties, that is correlated with positive subjective and psychological well-being.

KEYWORDS
consumer welfare, psychological well-being, social media, social platforms, social ties, subjective well-being

INTRODUCTION

Social platforms are digital services facilitating "social" communications for sharing information, keeping in touch with friends and family, accessing news and entertainment, and following people and companies (i.e., both traditional social media and messenger applications). They facilitate the daily interactions of billions of people globally.

Generally, the literature concludes that social platforms negatively affect people's overall subjective and psychological well-being (Appel et al., 2020; Huang, 2017). For example, Allcott et al. (2020) report social platform use negatively correlates with subjective well-being. Cramer and Inkster (2017) find social platforms harm youths' mental health. A study of teenagers found a negative correlation between self-reported social media use and overall life satisfaction (Orben et al., 2019). Further, Shakya and Christakis (2017) show a negative association between Facebook behavior (e.g., clicking links, status updates) and well-being. Other studies connect social platforms to adverse psychological effects including depression (Appel et al., 2016), envy (Krasnova et al., 2013; Lin & Utz, 2015), and mental overload (Maier et al., 2012).

Yet, nascent research links social platform usage with positive outcomes, which should improve well-being. Social platform use can increase the number (Valkenburg et al., 2006) and strength of social ties (Acquisti & Gross, 2006; Utz, 2015), facilitate authentic self-presentation (Bailey et al., 2020; Reinecke & Trepte, 2014), and provide social support during crisis (Greene et al., 2011; Laroche et al., 2012; Merolli et al., 2013). See Appendix S1 for an in-depth literature review.

In terms of physical health and financial security, the evidence is mixed. For physical health, social platform use is associated with poorer diets (Sina et al., 2022) and sleep quality (Woods & Scott, 2016). Yet, Nabi et al. (2013) find that support on a social platform decreased illness and using social platforms (vs. other relaxing activities) helped people return to a normal

Accepted by Thomss Kramer and Aparna Labroo, Editors; Associate Editor, Jesper Nielsen

heart rate and blood pressure faster following a stressor (Johnshoy et al., 2020). Concerning financial security, whereas social platform usage increases negative behaviors such as impulse shopping (Zafar et al., 2021; Zhang et al., 2018), Cao et al. (2020) demonstrate that using social platforms for personal finance management improves financial outcomes.

Unfortunately, much of the research on the relationship between social platform usage and subjective and psychological well-being is based on small or unrepresentative samples (e.g., adolescents) or is methodologically limited (e.g., self-reported, confounded). The current research sought to address these limitations by exploring the relationship between social platform use, subjective well-being, and its component factors using a robust empirical approach. We collect primary data using a large sample size of 1029 adults and a longitudinal study design that unobtrusively measures social platform usage. The 6-month longitudinal design demonstrates how changes in social platform usage correlate with subsequent well-being. While not causal, the design allows the exploration of time series effects (e.g., examine if well-being increases after a week of more social platform usage). Further, we unobtrusively measure social platform usage instead of relying on self-reports which eliminates potential biases (e.g., systematic underreporting of usage due to "mindless scrolling"), self-presentational concerns (e.g., concerns that high usage would make them look "bad"/"lazy") and demand effects (e.g., the negative effects of social media use have received substantial media attention so participants may want to "help" researchers confirm these effects). Finally, we explore potential explanations for our findings by classifying social media platforms by usage type and characteristics to better understand the important factors to the effect of social platform use on well-being. Resultantly, our research provides a sophisticated and contextualized analysis of the impact of social platform use, as manifested in the "real world" over time. This contribution is elucidated in Table 1.

Importantly, we show a small, positive correlational effect of time spent using social platforms on subjective and psychological well-being. This positive relationship is related to using platforms that facilitate intimate interactions, or using social platforms to engage with close ties (e.g., friends, family). While these findings contradict a large body of research that generally concludes that social platforms negatively affect people's well-being, it aligns with past research on real-world social relationships. Research on real-world relationships emphasizes the importance of social bonds and connectivity to improve well-being (e.g., Cohen, 2004; Holt-Lunstad et al., 2010; House et al., 1988; Lin et al., 1979; Rook, 1984; Vanderhorst & McLaren, 2005; Williams et al., 1981). Furthermore, it extends the growing literature that finds a positive effect of specific social platform behavior on well-being (e.g., reading a post written by a close tie; Lin & Utz, 2015, receiving personalized communication; Burke & Kraut, 2016). Finally, we show no relationship between social platform usage and physical health or financial security.

METHOD

We recruited 1293 Android mobile users from Prolific Academic. Participants followed an ethics board-approved procedure; they read and agreed to mobile application usage tracking. They installed an Android-compatible application, mLab, on their mobile device that unobtrusively tracked (i.e., participants did not actively participate in data-capture) the time participants spent using each application.

Participants completed an initial survey collecting demographic and socio-economic information (age, gender, income, employment status, marital status, education level, country, and language). Every subsequent 2 weeks for 6 months, participants responded to a follow-up survey in mLab for payment. In the initial and subsequent surveys, participants reported their overall subjective well-being using the "Cantril Life Ladder" (0–10 scale; Cantril, 1965; Appendix S2).

Psychological well-being was measured using eight items adapted from a longer psychological well-being scale (Ryff, 1989) to reduce attrition. A pretest determined the items with the highest commonalities (>0.70 threshold) in a principal component analysis. The resultant scale included "I feel supported by others", and "I am pleased with where my life is headed" (1 = strongly disagree to 7 = strongly agree; $\alpha = 0.95$; Appendix S2).

Physical health was measured using 11 items (7-point scale; e.g., "I have had a lot more energy of late" and "I consider myself to be in good health"; $\alpha = 0.85$) and financial security was measured with nine items (7-point scale; e.g., "I am satisfied with my current level of income"; $\alpha = 0.91$; see Appendix S3 for both scales). Additional scale development details and scale cross-correlations are provided in Appendices S4 and S5, respectively.

Occasionally, participants would take surveys after very long inter-survey gaps (e.g., a participant would let 6 weeks elapse and take the three available surveys back-to-back). We only included responses provided between 1 and 3 weeks after the completion of the preceding survey. Appendix S6 shows the robustness of this choice. Participants also reported gender, age, and any major life changes since the last survey. We removed three participants with impossible demographic deviations due to suspected deception.

To reduce the attrition rate, after eight surveys, the participants who had completed all surveys so far were notified that if they completed every remaining survey, they would receive a bonus payment. After exclusions, 1029 participants had usable observations from the study (20.42% attrition).

MLab collected application usage data on each participant's mobile device every 15 min from the Android OS

TABLE 1 Methodological contribution of our work.

Research	Sample size	Sample frame	Design	Context	Social platforms	Social platform usage type	Social platform measurement	Well-being measurement	Explanatory factors	Conclusion (direction of the relationship)
Our research	1029	Adults	Longitudinal	In situ	Multiple platforms	Time spent using	Unobtrusively, objectively measured	Subjective well-being and three component measures: Psychological well-being Physical health, Financial security	Socialness of platform interaction (i.e., whether users typically interact with intimate/close vs. distant others)	Positive (on Subjective and Psychological well-being)
Burke and Kraut (2016)	1910	Adults	Longitudinal	In situ	Facebook	Facebook communication logs	Unobtrusively, objectively measured	Psychological well-being	Personalized communication from strong ties	Positive
Kross et al. (2013)	82	University students	Longitudinal	In situ	Facebook	Amount of Facebook use	Self-reported	Subjective well-being	None	Negative
Shakya and Christakis (2017)	5208	Adults	Correlational	Sec-ondary data	Facebook	Friend count, Lifetime like count, 30-day link count, status count	Self-reported	Mental health, Life satisfaction	None	Negative
Orben et al. (2019)	12,672	Adolescents	Longitudinal	Secondary data	Multiple platforms	Time spent using	Self-reported	Life satisfaction	None	Negative
Allcott et al. (2020)	1646	Adults	Experiment	In situ	Facebook	Deactivated versus Not	Manipulated	Life satisfaction	None	Negative
Ostic et al. (2021)	940	Mexican university students	Correlational	Lab	Multiple platforms	Social media as part of daily life	Self-reported	Psychological well-being	Bonding and bridging social capital	Positive
Valkenburg et al. (2022)	353	Dutch university students	Longitudinal	In situ	Instagram, Snapchat	Browsing	Self-reported	Subjective well-being	Envy	Negative

TABLE 2 High-level App categories and shares of usage.

App category	Sample members	Average share of device usage
Social Platforms	Facebook, Facebook Messenger, Instagram, Pinterest, Reddit, Snapchat, Tumblr, Twitter, WhatsApp, YouTube	25.38%
Retail & Entertainment	Games, other on- and offline media, retailing apps	25.99%
Information	Browser, News & Weather, Maps & Navigation, Search	16.86%
Communication	Contact list managers, Dialer apps, Texting apps	4.58%
Productivity	Office & Email apps	4.06%
Miscellaneous	Home screen & other system apps, Finance & Banking, Antivirus, Health & Fitness apps	12.35%
Uncategorized		10.78%

TABLE 3 Estimation results, basic model.

Subjective well-being	Model 1	Model 2	Model 3
SWB (lagged)	0.7732 (0.0178)***	0.7350 (0.0188)***	0.7304 (0.0191)***
Total SP use	0.0045 (0.0017)**	0.0069 (0.0022)**	0.0068 (0.0022)**
Total device use		−0.0057 (0.0033)†	−0.0052 (0.0034)
Positive life event			0.0576 (0.0114)***
Negative life event			−0.1039 (0.0138)***
Const.	0.3990 (0.0336)***	0.5253 (0.0532)***	0.5280 (0.0538)***
Demographic and Socio-economic controls	No	Yes	Yes
Obs.	8335	8335	8335
R^2	0.5867	0.5952	0.6017

Note: Standard errors are in parentheses.
***$p<0.001$, **$p<0.01$, *$p<0.05$, †$p<0.1$.

application usage logs. The raw application usage data was a record of the amount of time (in milliseconds) each application spent in the foreground (i.e., open and in use) scaled to 24h (e.g., if 30min usage for a preceding 36-h interval was reported, it was rescaled to 20min usage over 24-h). We discarded observations reporting more than eight (of 24) hours of foreground time for a single application; these were identified as technical errors and affected fewer than 0.4% of observations. A robustness analysis with alternative exclusion criteria (i.e., 6 and 10h) demonstrated the robustness of our findings (see Appendix S7).

The resulting application usage data included 21,587 unique mobile applications. We categorized the most-used applications by looking up their names and descriptions and then assigning them to one of the categories listed in Table 2. A total of 1566 apps, accounting for 89.22% of all device usage time, were categorized. Importantly, social platform applications in the dataset were Facebook, Facebook Messenger, Google+, Imgur, Instagram, LinkedIn, Pinterest, Reddit, Skype, Snapchat, Spotify, Tumblr, Twitter, WhatsApp, and YouTube, reflective of the time of data collection.

To calculate application usage time, we used a greedy algorithm that selected the most non-overlapping app usage observations available (to avoid double-counting) during the 7days before each biweekly survey and calculated daily average usage per application. Application-level usage was transformed into category-level usage by summing, within participant, the times spent in the applications within each category.

RESULTS

We estimated several time series regression models. In Models 1–3 (Table 3), the natural logarithm of subjective well-being measured in survey t was regressed on the natural logarithm of average time spent using social platforms in the week prior to survey t. We included the following control variables in the regression: (i) the natural logarithm of subjective well-being measured in the previous survey ($t-1$) to allow for a carry-over or state-dependent effect of subjective well-being between surveys (each model); (ii) the average total daily time spent on the mobile device during the week preceding survey t (Models 2–3); (iii) demographic and socio-economic control variables relevant to well-being (Models 2–3); and (iv) indicators of positive and negative major life events reported by participants in survey t (two variables, with one variable of each type, Model 3; for life event coding and frequency see Appendix S8). To ensure the natural logarithm was defined for each variable in the analysis,

TABLE 4 Summary of variables.

Variable	Description		*M* (SD)
Well-being			
PsyWB	Psychological well-being; eight-item subjective measure of one's personal situation		4.84 (1.29)
PhyH	Physical health; 11-item subjective measure of one's health situation		4.07 (1.08)
FinS	Financial security; nine-item subjective measure of one's financial situation		4.02 (1.34)
SWB	Subjective well-being; one-item Cantril Life Ladder measuring best to worst possible life (Worst=0, Best=10)		5.92 (1.82)
Social platform use			
Total SP use	Total time spent on social platforms (in minutes)		77.27 (82.89)
Intimate social interaction	Time spent on Facebook, Facebook Messenger, Skype, Snapchat, and WhatsApp (in minutes)		45.88 (62.67)
Moderately social interaction	Time spent on Google+, Instagram, and Spotify (in minutes)		5.87 (15.68)
Distant social interaction	Time spent on Imgur, LinkedIn, Pinterest, Reddit, Tumblr, Twitter, and YouTube (in minutes)		25.52 (47.90)
Other			
Device use	Total usage time (in minutes)		303.40 (230.33)
Positive life event	Positive life event		3.14%
Negative life event	Negative life event		5.53%
Individual characteristics			
Age	Age (in years)		33.96 (10.35)
Gender	Female=1, Male=0		61.52%
Education	Highest degree completed	1=high school or less	15.06%
		2=some college or completed bachelors	69.97%
		3=masters or professional degree	13.41%
		4=PhD	1.55%
Work	Employment status	1=working	69.00%
		2=not working but searching	5.15%
		3=not working	15.16%
		4=student	1.36%
		5=not specified	9.33%
Relationship	Marital status	1=married	37.03%
		2=widowed	1.07%
		3=divorced	5.25%
		4=separated	2.14%
		5=never married	53.94%
		6=prefer not to say	0.58%
Country	Country of residence	1=U.K.	58.21%
		2=U.S.	26.82%
		3=neither	14.97%
Income	Household income level (12 levels; below \$10,000 to greater than \$150,000 (below £10,000 to greater than £150,000 participants)		4.29 (2.62)
Language	Primary spoken language (English=1, Other=0)		89.21%

each of the subjective well-being and all device (including social platforms) use variables were increased by one unit, respectively. The variables used in the analysis are described in Table 4.

All models controlled for common seasonal shocks via survey-number dummy variables. To control for time-invariant respondent heterogeneity, robust standard errors clustered by respondent were estimated.

The effect of prior-period social platform usage on current-period subjective well-being was positive and significant ($B=0.0068$, $SE=0.0022$, $p=0.002$). Not surprisingly, there was a strong positive carry-over effect of lagged subjective well-being on current subjective well-being ($B=0.7304$, $SE=0.0191$, $p<0.001$). The above results are from the regression featuring all control variables (i.e., Model 3) but the main results are similar across Models 1–3. The results are presented in Table 3.

Subjective well-being is a coarse measure based on a single-item scale and our goal was to better determine what components of subjective well-being are impacted by social platform usage. To analyze the effect of social platforms on the components of subjective well-being, three sets of additional models were estimated, using the natural logarithm of psychological well-being, physical health, and financial security, respectively, as the dependent measures replacing the natural logarithm of subjective well-being in Models 1–3. We controlled for the natural logarithm of both subjective well-being and the measure of the dependent variable in the previous survey ($t-1$). For example, when estimating the impact of social platform usage on psychological well-being, the model controlled for the natural logarithms of both prior-period subjective well-being and prior-period psychological well-being.

For brevity, the reported results focus on the full models (Models 6, 9, and 12). The findings show a significant positive effect of prior-period social platform usage on current-period psychological well-being ($B=0.0050$, $SE=0.0018$, $p=0.005$). However, there was no significant effect of the same variable on current-period physical health ($B=0.0005$, $SE=0.0020$, $p=0.80$) or current-period financial security ($B=0.0004$, $SE=0.0020$, $p=0.86$). Each model had a strong carry-over effect of the lagged dependent variable. Lagged psychological well-being had a significant effect in Model 6 ($B=0.7896$, $SE=0.204$, $p<0.001$), lagged physical health in Model 9 ($B=0.6679$, $SE=0.149$, $p<0.001$), and lagged financial security in Model 12 ($B=0.8097$, $SE=0.0118$, $p<0.001$). Additionally, lagged subjective well-being was significant in all models ($B=0.0749$, $SE=0.0169$, $p<0.001$ in Model 6, $B=0.0490$, $SE=0.0110$, $p<0.001$ in Model 9, and $B=0.0696$, $SE=0.0117$, $p<0.001$ in Model 12). The results are presented in Table 5.

Follow-up analyses

Our results provide correlational evidence that time spent on social platforms is positively related to subjective well-being and, more specifically, psychological well-being (but not physical health or financial security as other dimensions of well-being). Next, we explored how the usage and characteristics of social platforms were related to subjective and psychological well-being. This was not straightforward because for privacy reasons we did not record what participants did when using social platforms. To address this issue, we collected participants' perceptions of typical usage and platform characteristics in a separate pretest and used these to classify platforms.

The pretest from the same time period as the main study asked 101 MTurk participants to first identify which of 17 social platforms they used (e.g., Facebook, Instagram, Twitter, Snapchat). Then participants rated each platform they used on nine social platform dimensions deemed important from the literature. For platform usage type, three usage measures were included: the activeness of interaction (Khan, 2017; Pagani & Malacarne, 2017; Trifiro & Gerson, 2019), the socialness of platform interaction (i.e., whether users typically interact with intimate/close vs. distant others; Gilbert & Karahalios, 2009; Krämer et al., 2014; Vriens & van Ingen, 2018), and the directedness of the communication (i.e., one-way vs. two-way; O'Sullivan & Carr, 2018). For platform characteristics, six characteristics were included: content format (i.e., primarily text-based vs. primarily image-based; Kaplan & Haenlein, 2010), personalness (i.e., personalized vs. impersonal; Bazarova & Choi, 2014), emotionality (Hassouneh & Brengman, 2014), popularity (i.e., mainstream vs. niche; Boyd & Ellison, 2007), levity (i.e., serious vs. fun; Xu et al., 2012), and stimulation (i.e., exciting vs. boring; Barash et al., 2010; Utz, 2015).

Along each of the nine dimensions, we grouped the social platforms into three tiers using the thresholds of one standard deviation above and below the mean score on the given dimension, respectively. The resulting classification of platforms is presented in Table 6. Next, we calculated the cumulative daily usage time of all social platform apps in each of the resulting 27 groups (i.e., 9 dimensions $\times$ 3 tiers) preceding each well-being survey. Finally, we replaced our total social platform usage variable with the so-derived 27 variables reflecting usage type or platform characteristics and estimated a rigorous lasso procedure (Belloni et al., 2012) to identify which of these 27 variables were likely the most important potential drivers of the psychological well-being dependent variable (for procedural details and results see Appendix S9). This analysis revealed that the use of platforms offering "intimate" interactions was most correlated with psychological well-being among the 27 variables. The platforms classified as offering intimate interactions were Facebook, Skype, Snapchat, and WhatsApp.

The findings from the lasso model informed the specifications for Models 13–15. These models matched the specifications of Models 4–6, but instead of using a single aggregate measure of all social platform use, Models 13–15 used three lagged social platform usage variables. The first variable was for intimate interactions (high in Table 6), defined as used primarily for interacting with intimate/close ties. The second variable was for moderately social interactions (neutral in Table 6), meaning people use those platforms to interact with both intimate ties and distant others. Finally, the third variable was for distant interactions (low in Table 6) or interacting primarily with

TABLE 5 Estimation results, modeling different aspects of well-being.

Dependent variable	Psychological well-being			Physical health			Financial security		
	Model 4	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
SWB (lagged)	0.0843 (0.0163)***	0.0767 (0.0169)***	0.0749 (0.0169)***	0.0469 (0.0098)***	0.0519 (0.0110)***	0.0490 (0.0110)***	0.0819 (0.0115)***	0.0715 (0.0118)***	0.0696 (0.0117)***
PsyWB (lagged)	0.7981 (0.0202)***	0.7899 (0.0204)***	0.7896 (0.0204)***						
PhyH (lagged)				0.6893 (0.0149)***	0.6720 (0.0147)***	0.6679 (0.0149)***			
FinS (lagged)							0.8235 (0.0111)***	0.8097 (0.0118)***	0.8097 (0.0118)***
Total SP Use	0.0030 (0.0014)*	0.0050 (0.0018)**	0.0050 (0.0018)**	−0.0045 (0.0016)*	0.0005 (0.0020)	0.0005 (0.0020)	−0.0025 (0.0014)†	0.0004 (0.0020)	0.0004 (0.0020)
Total Device Use		−0.0049 (0.0028)†	−0.0048 (0.0028)†		−0.0054 (0.0030)†	−0.0048 (0.0030)		−0.0039 (0.0032)	−0.0037 (0.0032)
Positive Life Event			0.0466 (0.0114)***			0.0115 (0.0130)			0.0371 (0.0118)**
Negative Life Event			−0.0430 (0.0098)***			−0.1047 (0.0108)***			−0.0408 (0.0111)***
Const.	0.1314 (0.0232)***	0.1647 (0.0364)***	0.1638 (0.0366)***	0.3501 (0.0249)***	0.3698 (0.0402)***	0.3796 (0.0405)***	0.0933 (0.0182)***	0.1531 (0.0323)***	0.1529 (0.0323)***
Demographic and Socio-economic controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Obs.	8335	8335	8335	8335	8335	8335	8335	8335	8335
R^2	0.7174	0.7192	0.7206	0.5172	0.5219	0.5295	0.7389	0.7411	0.7420

Note: Standard errors are in parentheses.
***p<0.001, **p<0.01, *p<0.05, †p<0.1.

TABLE 6 Social platform app classificatons based on the pretest results.

Name and description	High (+1 SD)	Neutral	Low (−1 SD)
Usage type			
SP Scale 1: Activeness of interaction	*Active* Skype, WhatsApp	*Moderate* Facebook, Instagram, Twitter, Google+, Snapchat, LinkedIn, Pinterest, Tumblr, Reddit, Imgur	*Passive* YouTube, Spotify
SP Scale 2: Socialness of interactions	*Intimate* (i.e., *Close Ties*) Facebook, Skype, Snapchat, WhatsApp	*Moderate* Instagram, Google+, Spotify	*Distant* (i.e., *Distant Ties*) YouTube, Twitter, LinkedIn, Pinterest, Tumblr, Reddit, Imgur
SP Scale 3: Directedness of interaction	*Two-Way Communication* Skype, WhatsApp	*Moderate* Facebook, Instagram, Twitter, Google+, Snapchat, LinkedIn, Reddit	*One-Way Communication* YouTube, Spotify, Pinterest, Tumblr, Imgur
Platform characteristics			
SP Scale 4: Content format	*Image-Based* YouTube, Instagram, Skype, Snapchat, Pinterest, Imgur	*Moderate* Facebook, Spotify, Tumblr	*Text-Based* Twitter, Google+, LinkedIn, WhatsApp, Reddit
SP Scale 5: Personalness	*Personal* Skype, WhatsApp	*Moderate* Facebook, Instagram, Twitter, Google+, Snapchat, LinkedIn, Spotify, Pinterest, Tumblr	*Impersonal* YouTube, Reddit, Imgur
SP Scale 6: Emotionality	*Emotion-Based* Snapchat, Tumblr	*Moderate* Facebook, YouTube, Instagram, Twitter, Skype, Spotify, Pinterest, WhatsApp, Imgur	*Information-Based* Google+, LinkedIn, Reddit
SP Scale 7: Popularity	*Mainstream*	*Moderate* Facebook, YouTube, Instagram, Twitter, Skype, Snapchat, Spotify, Pinterest, WhatsApp, Reddit, Imgur	*Niche* Google+, LinkedIn, Tumblr
SP Scale 8: Levity	*Fun* Snapchat	*Moderate* Facebook, YouTube, Instagram, Twitter, Skype, Spotify, Pinterest, Tumblr, WhatsApp, Reddit, Imgur	*Serious* Google+, LinkedIn
SP Scale 9: Stimulation	*Exciting*	*Moderate* Facebook, YouTube, Instagram, Twitter, Skype, Snapchat, Spotify, Pinterest, Tumblr, WhatsApp, Reddit, Imgur	*Boring* Google+, LinkedIn

Note: Four platforms (Sina Weibo, Viber, YY, and Periscope) were not analyzed because three or fewer people used them.

distant others. The share of time participants spent on social platforms in each category is reported in Table 2.

The results for Models 13–15 are reported in Table 7. Estimating separate coefficients for the impact of intimate and other social platform usage (Model 15), findings show a significant positive relationship between prior-period intimate social platform usage and current-period psychological well-being ($B=0.0075$, $SE=0.0016$, $p<0.001$). The effects of prior-period moderate and distant social platform usage on current psychological well-being were not significant ($B_{Moderate}=-0.0017$, $SE=0.0021$, $p=0.42$ and $B_{Distant}=0.0006$, $SE=0.0015$, $p=0.69$). As before, there was a strong positive carry-over effect of lagged psychological well-being on current psychological well-being ($B=0.7869$, $SE=0.0204$, $p<0.001$), and lagged overall subjective well-being ($B=0.0738$, $SE=0.0168$, $p<0.001$).

Finally, Models 16–18 replaced the lagged social platform usage variable in Models 1–3 with the three social platform usage variables from Models 13–15. Thus, the natural logarithm of subjective well-being was regressed on the intimate, moderately, and distant social interaction variables using the same controls as detailed in Models 1–3. The results showed, as with psychological well-being, there is a significant positive relationship between prior-period intimate social interactions platform usage on current subjective well-being (Appendix S10).

DISCUSSION

The 6-month longitudinal study showed a small, positive correlation between time spent using social platforms

TABLE 7 Estimation results, social platform use split along socialness of interactions dimension.

Psychological well-being	Model 13	Model 14	Model 15
SWB (lagged)	0.0819 (0.0162)***	0.0756 (0.0168)***	0.0738 (0.0168)***
PsyWB (lagged)	0.7950 (0.0199)***	0.7871 (0.0204)***	0.7869 (0.0204)***
Intimate social interactions	0.0061 (0.0013)***	0.0076 (0.0016)***	0.0075 (0.0016)***
Moderately social interactions	−0.0020 (0.0020)	−0.0017 (0.0020)	−0.0017 (0.0021)
Distant social interactions	−0.0012 (0.0014)	0.0006 (0.0015)	0.0006 (0.0015)
Total device use		−0.0060 (0.0027)*	−0.0058 (0.0027)*
Positive life event			0.0459 (0.0115)***
Negative life event			−0.0429 (0.0098)***
Const.	0.1384 (0.0229)***	0.1705 (0.0365)***	0.1695 (0.0367)***
Demographic and Socio-economic controls	No	Yes	Yes
Obs.	8335	8335	8335
R^2	0.7180	0.7197	0.7211

Note: Standard errors are in parentheses.
***$p<0.001$, **$p<0.01$, *$p<0.05$, †$p<0.1$.

in the prior week and subsequently reported subjective and psychological well-being. Further investigation revealed that this is related to the socialness of the interaction. Time spent using social platforms that primarily facilitate interactions with intimate social ties is positively related to subjective and psychological well-being. These findings are important because they result from a rigorous investigation of the real-world impact of social platform use on well-being over time. This is the first study that examines the connection between measured time spent using social platforms (vs. measures of specific online behaviors; Bailey et al., 2020; Burke & Kraut, 2016; Shakya & Christakis, 2017) and well-being.

Moreover, our research reopens a debate that has largely been treated as solved and adds to the small but growing literature that finds a positive effect of social platform usage on well-being (e.g., people felt happier after reading a Facebook post written by a close friend or family member; Lin & Utz, 2015, receiving personalized communication from strong ties on Facebook was associated with improvements in well-being; Burke & Kraut, 2016, social media boosted psychological well-being due to bonding; Ostic et al., 2021), with ours being the first to look at time spent using social platforms. Adjacently, smartphones have been shown to induce psychological comfort (Melumad & Pham, 2020) because of their association with facilitating social interactions with loved ones (Aoki & Downes, 2003). Further, this is consistent with decades of research on real-world social relationships demonstrating how meaningful relationships and social engagement positively contribute to well-being (e.g., Cohen, 2004; Lin et al., 1979; Rook, 1984; Vanderhorst & McLaren, 2005; Williams et al., 1981). Therefore, when social platforms enhance social relationships (cf. Utz, 2015; Valkenburg et al., 2006), spending time on them is related to increased subjective and psychological well-being. Yet, when people spend time on social platforms to engage with acquaintances, or on platforms distinguished by other usage types (i.e., activeness or directedness of interactions) or characteristics (e.g., content format, personalness), there is no relationship to well-being.

However, it is important to put these findings into context; the positive effect of time spent using social platforms on subsequent subjective and psychological well-being is detectable but small. Unsurprisingly, other contributors to well-being that were controlled for (e.g., working, sleeping) are more important, and, similarly, major life events can be bigger "shocks" to well-being (Kettlewell et al., 2020).

Notably, the findings did not show any effects of using social media platforms on physical health and financial security. This is likely due to the effect sizes being comparatively small and the relatively short time scale used in our research, wherein the impacts of social platform usage on health and finances may take years to manifest. Also, in the case of physical health, the lack of effect is not entirely surprising as several randomized controlled studies failed to show a significant effect of reducing electronics usage on physical activity (Babic et al., 2016; Hinkley et al., 2015; Mhurchu et al., 2009).

These findings are relevant to many stakeholders. For consumers, it is important to understand that changing usage habits to focus on intimate connections may enhance well-being. From a public policy standpoint, heavy legislative control may be unnecessary. Further, technology companies can safeguard their users by implementing content prioritization strategies (e.g., Meta's algorithms should prioritize content from family over influencers) and other corporations could focus on facilitating likeminded customer-to-customer connections based on shared interests.

LIMITATIONS

A limitation of our research is that mLab only tracked mobile device app usage, not what users did while using those apps due to participant privacy. Therefore, while we used pretesting to infer how intimate interactions were at an app level, a more fine-grained measure of specific behaviors was not available. Another limitation is we were unable to account for social platform usage that occurred on other devices not registered with the study. However, mobile devices are primarily how users access social platforms (Villanti et al., 2017) and there is a correlation between how people use mobile and non-mobile devices (Kane et al., 2009). Thus, social platform usage on the registered device is an acceptable relative measure, even if an inaccurate measure of total social platform usage.

Finally, recruiting only Android users due to technology constraints and English speakers could limit the generalizability of the findings. On the first point, we ran a post-test comparing Android and iPhone users on socio-economic and demographic variables and found financial and income differences (see Appendix S11) with iPhone users reporting higher income (consistent with Sharma (2011)), which may impact financial security and finance-related stresses on well-being (Ullah, 1990). To address this concern, our models control for income. Yet, we cannot say anything about generalizability beyond English speakers, due to lack of information.

FUTURE DIRECTIONS

Past literature primarily reports a negative relationship between social platform usage and well-being. Contrastingly, we find a small, positive effect. This highlights the importance of future research that identifies moderators that determine when social platform usage is positive versus negative. For example, we identify socialness of the platform (i.e., intimate ties), but future research could measure perceptions of intimacy following using the social platform. Age may be another key moderator; a majority of past research reporting a negative relationship focused on adolescents who are more likely to make negative social comparisons, be cyberbullied, and experience fear of missing out (FOMO) (Cramer & Inkster, 2017). While our effect holds across all adult age groups (see Appendix S12), future research could explore at what age these effects reverse. Further, situational factors (e.g., politics; Allcott et al., 2020) and behavioral usage type (e.g., status updates; Shakya & Christakis, 2017) could moderate the relationship. Thus, we hope to reopen the debate on the relationship between social platform usage and well-being and encourage further exploration into factors influencing it.

While our findings offer some insight into the relationship between social platforms and subjective and psychological well-being, future research is needed to identify how a variety of newer technologies impact well-being. New technologies hold the promise of facilitating even greater intimate social connections such as videotelephony software that allows access to the facial expressions and voice of our interaction partners, the popularity of multiplayer gameplay that allows gamers to collaborate in teams, and even the growing prevalence of the metaverse where virtual reality and spatial audio emulates non-digital social environments and can create a sense of "being there". Based on our findings, any technology-mediated intimate social interactions should bolster well-being, but future research is necessary to explore not just the extent of this effect, but how other technology-specific factors may shape the relationship.

More broadly, it is interesting to investigate if and how newer technologies can replace in-person socialization. Specifically, do the positive effects of social platform use hinge on the prior development of non-digital intimate relationships? Are we in the psychological "sweet spot" where our digital communications augment prior non-digital relationships? If so, given that we are spending more time than ever before socializing online, in the future will we still forge strong enough intimate ties to take advantage of the positive effects of social platform use? These important questions merit ongoing investigation.

ACKNOWLEDGEMENTS

This research was funded by the John Fell Fund at the University of Oxford, the Henry Crown Institute of Business Research in Israel at Tel Aviv University, the Marketing Science Institute, Deutsche Forschungsgemeinschaft, and internal research funds at the Saïd Business School, University of Oxford. Funds from corporations were not used for this research. The authors thank William Fritz for his help with data collection, Richard Lutz, Inyoung Chae, Felipe Thomaz, and Jacob Goldenberg for their comments and suggestions, and seminar participants at Georgia University of Technology, Interdisciplinary Center, Singapore Management University, University of Oxford, Warwick University, University of Florida, Goethe University Frankfurt, Ludwig Maximilian University of Munich, and University of Sussex.

DATA AVAILABILITY STATEMENT

Our data and associated files are on the OSF data repository: https://osf.io/gpyqb/?view_only=baeead1c3f9f45aa82b9887a178461ef.

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REFERENCES

Acquisti, A., & Gross, R. (2006). Imagined communities: Awareness, information sharing, and privacy on the Facebook. In G. Danezis & P. Golle (Eds.), *Privacy enhancing technologies* (pp. 36–58). Springer.

Allcott, H., Braghieri, L., Eichmeyer, S., & Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, *110*(3), 629–676.

Aoki, K., & Downes, E. (2003). An analysis of young people's use of and attitudes toward cell phones. *Telematics and Informatics*, *20*(4), 349–364.

Appel, H., Gerlach, A. L., & Crusius, J. (2016). The interplay between Facebook use, social comparison, envy, and depression. *Current Opinion in Psychology*, *9*, 44–49.

Appel, M., Marker, C., & Gnambs, T. (2020). Are social media ruining our lives? A review of meta-analytic evidence. *Review of General Psychology*, *24*(1), 60–74.

Babic, M. J., Smith, J. J., Morgan, P. J., Lonsdale, C., Plotnikoff, R. C., Eather, N., Skinner, G., Baker, A. L., Pollock, E., & Lubans, D. R. (2016). Intervention to reduce recreational screen-time in adolescents: Outcomes and mediators from the "Switch-Predicting tie strength with social media. *Proceedings* ff 4 Healthy Minds" (S4HM) cluster randomized controlled trial. *Preventive Medicine*, *91*, 50–57.

Bailey, E. R., Matz, S. C., Youyou, W., & Iyengar, S. S. (2020). Authentic self-expression on social media is associated with greater subjective well-being. *Nature Communications*, *11*, 4889.

Barash, V., Ducheneaut, N., Isaacs, E., & Bellotti, V. (2010). Faceplant: Impression (mis)management in Facebook status updates. *ICWSM. Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*.

Bazarova, N. N., & Choi, Y. H. (2014). Self-disclosure in social media: Extending the functional approach to disclosure motivations and characteristics on social network sites. *Journal of Communication*, *64*(4), 635–657.

Belloni, A., Chen, D., Chernozhukov, V., & Hansen, C. (2012). Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica*, *80*(6), 2369–2429.

Boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230.

Burke, M., & Kraut, R. E. (2016). The relationship between Facebook use and well-being depends on communication type and tie strength. *Journal of Computer-Mediated Communication*, *21*(4), 265–281.

Cantril, H. (1965). *The patterns of human concern*. Rutgers University Press.

Cao, Y., Gong, F., & Zeng, T. (2020). Antecedents and consequences of using social media for personal finance. *Journal of Financial Counseling and Planning*, *31*(1), 162–176.

Cohen, S. (2004). Social relationships and health. *American Psychologist*, *59*(8), 676–684.

Cramer, S., & Inkster, B. (2017). #StatusOfMind: Social media and young people's mental health and wellbeing. RSPH: Royal Society for Public Health Vision, Voice, and Practice, May, 1–32.

Gilbert, E., & Karahalios, K. (2009). Predicting tie strength with social media. Proceedings of the 27th International Conference on human factors in computing systems, ACM Press.

Greene, J. A., Choudry, N. K., Kilabuk, E., & Shrank, W. H. (2011). Online social networking by patients with diabetes: A qualitative evaluation of communication with Facebook. *Journal of General Internal Medicine*, *26*, 287–292.

Hassouneh, D., & Brengman, M. (2014). A motivation-based typology of social virtual world users. *Computers in Human Behavior*, *33*, 330–338.

Hinkley, T., Cliff, D. P., & Okely, A. D. (2015). Reducing electronic media use in 2-3 year-old children: Feasibility and efficacy of the Family@play pilot randomised controlled trial. *BMC Public Health*, *15*(779), 1–12.

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *Public Library of Science Medicine*, *7*(7), 1–20.

House, J. S., Umberson, D., & Landis, K. R. (1988). Structures and processes of social support. *Annual Review of Sociology*, *14*, 293–318.

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *20*(6), 345–404.

Johnshoy, Q., Moroze, E., Kaser, I., Tanabe, A., Adkisson, C., Hutzley, S., Cole, C., Garces, S., Stewart, K., & Campisi, J. (2020). Social media use following exposure to an acute stressor facilitates recovery from the stress response. *Physiology & Behavior*, *223*, 113012.

Kane, S. K., Karlson, A. K., Meyers, B. R., Johns, P., Jacobs, A., & Smith, G. (2009). Exploring cross-device web use on PCs and mobile devices. In *Human-Computer Interaction – INTERACT* (pp. 722–735). Springer.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*(1), 59–68.

Kettlewell, N., Morris, R. W., Ho, N., Cobb-Clark, D. A., Cripps, S., & Glozier, N. (2020). The differential impact of major life events on cognitive and affective wellbeing. *SSM-Population Health*, *10*, 100533.

Khan, M. L. (2017). Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior*, *66*, 236–247.

Krämer, N. C., Rösner, L., Eimler, S. C., Winter, S., & Neubaum, G. (2014). Let the weakest link go! Empirical explorations on the relative importance of weak and strong ties on social networking sites. *Societies*, *4*(4), 785–809.

Krasnova, H., Wenningger, H., Widjaja, T., & Buxmann, P. (2013). Envy on Facebook: A hidden threat to users' life satisfaction? 11th International Conference on Wirtschaftsinformatik.

Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., Shablack, H., Jonides, J., & Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *Public Library of Science one*, *8*(8), e69841.

Laroche, M., Habibi, M. R., Richard, M.-O., & Sankaranarayanan, R. (2012). The effects of social media based brand communities on brand community markers, value creation practices, brand trust and brand loyalty. *Computers in Human Behavior*, *28*, 1755–1767.

Lin, N., Ensel, W. M., Simeone, R. S., & Kuo, W. (1979). Social support, stressful life events, and illness: A model and an empirical test. *Journal of Health and Social Behavior*, *20*, 108–119.

Lin, R., & Utz, S. (2015). The emotional responses of browsing Facebook: Happiness, envy, and the role of tie strength. *Computers in Human Behavior*, *52*, 29–38.

Maier, C., Laumer, S., Eckhardt, A., & Weitzel, T. (2012). Online social networks as a source and symbol of stress: An empirical analysis. In *Proceedings of the international conference on information systems, Orlando, FL: Association for Information Systems* (pp. 1–19).

Melumad, S., & Pham, M. T. (2020). The smartphone as a pacifying technology. *Journal of Consumer Research*, *47*(2), 237–255.

Merolli, M., Gray, K., & Martin-Sanchez, F. (2013). Health outcomes and related effects of using social media in chronic disease management: A literature review and analysis of affordances. *Journal of Biomedical Informatics*, *46*(6), 957–969.

Mhurchu, C. N., Roberts, V., Maddison, R., Dorey, E., Jiang, Y., Jull, A., & Tin, S. T. (2009). Effect of electronic time monitors on children's television watching: Pilot trial of a home-based intervention. *Preventive Medicine*, *49*(5), 413–417.

Nabi, R. L., Prestin, A., & So, J. (2013). Perceptions of social support, stress, and well-being. *Cyberpsychology, Behavior, and Social Networking*, *16*(10), 721–727.

Orben, A., Dielin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the*

National Academy of Sciences of the United States of America, *116*(21), 10226–10228.
Ostic, D., Qalati, S. A., Barbosa, B., Shah, S. M. M., Vela, E. G., Herzallah, A. M., & Liu, F. (2021). Effects of social media use on psychological well-being: A mediated model. *Frontiers in Psychology*, *12*, 678766.
O'Sullivan, P. B., & Carr, C. T. (2018). Masspersonal communication: A model bridging the mass-interpersonal divide. *News Media & Society*, *20*(3), 1161–1180.
Pagani, M., & Malacarne, G. (2017). Experiential engagement and active vs. passive behavior in mobile location-based social networks: The moderating role of privacy. *Journal of Interactive Marketing*, *37*, 133–148.
Reinecke, L., & Trepte, S. (2014). Authenticity and well-being on social network sites: A two-wave longitudinal study on the effects of online authenticity and the positivity bias in SNS communication. *Computers in Human Behavior*, *30*, 95–102.
Rook, K. S. (1984). The negative side of social interaction: Impact on psychological well-being. *Journal of Personality and Social Psychology*, *46*(5), 1097–1108.
Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081.
Shakya, H. B., & Christakis, N. A. (2017). Association of Facebook use with compromised well-being: A longitudinal study. *American Journal of Epidemiology*, *185*(3), 203–211.
Sharma, K. (2011). Android in opposition to iPhone. *International Journal on Computer Science and Engineering*, *3*(5), 1965–1969.
Sina, E., Boakye, D., Christianson, L., Ahrens, W., & Hebestreit, A. (2022). Social media and children's and adolescents' diets: A systematic review of the underlying social and physiological mechanisms. *Advances in Nutrition*, *13*(3), 913–937.
Trifiro, B. M., & Gerson, J. (2019). Social media usage patterns: Research note regarding the lack of universal validated measures for active and passive use. *Social Media + Society*, *5*(2), 1–4.
Ullah, P. (1990). The association between income, financial strain and psychological well-being among unemployed youths. *Journal of Occupational Psychology*, *63*(4), 317–330.
Utz, S. (2015). The function of self-disclosure on social network sites: Not only intimate, but also positive and entertaining self-disclosures increase the feeling of connection. *Computers in Human Behavior*, *45*, 1–10.
Valkenburg, P. M., Beyens, I., Pouwels, J. L., van Driel, I. I., & Keijsers, L. (2022). Social media browsing and adolescent well-being: Challenging the 'Passive Social Media Use Hypothesis. *Journal of Computer-Mediated Communication*, *27*(1), zmab015.
Valkenburg, P. M., Peter, J., & Schouten, A. P. (2006). Friend networking sites and their relationship to adolescents' well-being and social self esteem. *Cyberpsychology & Behavior*, *9*(5), 584–590.
Vanderhorst, R. K., & McLaren, S. (2005). Social relationships as predictors of depression and suicidal ideation in older adults. *Aging & Mental Health*, *9*(6), 517–525.
Villanti, A. C., Johnson, A. L., Ilakkuvan, V., Jacobs, M. A., Graham, A. L., & Rath, J. M. (2017). Social media use and access to digital technology in US young adults in 2016. *Journal Medical Internet Research*, *19*(6), e196.
Vriens, E., & van Ingen, E. (2018). Does the rise of the internet bring erosion of strong ties? Analyses of social media use and changes in core discussion networks. *News Media & Society*, *20*(7), 2432–2449.
Williams, A. W., Ware, J. E., & Donald, C. A. (1981). A model of mental health, life events, and social supports applicable to general populations. *Journal of Health and Social Behavior*, *22*, 324–336.
Woods, H. C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *Journal of Adolescence*, *51*, 41–49.
Xu, C., Ryan, S., Prybutok, V., & Wen, C. (2012). It is not for fun: An examination of social network site usage. *Information & Management*, *49*(5), 210–217.
Zafar, A. U., Qiu, J., Li, Y., Wang, J., & Shahzad, M. (2021). The impact of social media celebrities' posts and contextual interactions on impulse buying in social commerce. *Computers in Human Behavior*, *115*, 106178.
Zhang, K. Z. K., Xu, H., Zhao, S., & Yu, Y. (2018). Online reviews and impulse buying behavior: The role of browsing and impulsiveness. *Internet Research*, *28*(3), 522–543.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Crolic, C., Zubcsek, P. P., Stephen, A. T., & Brooks, G. (2025). Social platform use and psychological well-being. *Journal of Consumer Psychology*, *35*, 463–474. https://doi.org/10.1002/jcpy.1437