The Associations among Social Media Use, Young Adults' Well-being, and Health During and After the COVID-19 Pandemic: The Moderating Roles of Motivation

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Abstract

The purpose of this study was to first test the impact of the COVID-19 pandemic on Social Media Use and Social Media addiction among young adults by measuring two representative time periods during the pandemic: when the pandemic had just broken out and most people were in some form of lockdown, and when most US universities resumed in-person classes 12 months later. In addition, the study examined the bidirectional associations between Social Media Usage (SMU) and mental health among young adults. We also explored whether these associations were moderated by are moderated by the particular motivations of the person for using social media, such as to maintain social connections with friends or family, for entertainment, or for self-expression. Findings of our study suggested that young adults used social media more frequently at T1, likely due to quarantine restrictions. However, as normal attendance resumed, their social media usage decreased. Those who exhibited addiction to social media had poorer mental and physical health, although this association did not differ significantly between low and high addiction groups. At T1, there was a strong negative correlation between social media use intensity and mental health, which weakened or disappeared by T2. Social Activity was the main motivating factor negatively affecting young adults' health, but the impact varied across different social media platforms and their functions.

By April 2020, the World Health Organization (WHO) had already reported over 555,581 cases of COVID-19 in 216 countries or territories, with almost 40,455 deaths. In response, governments worldwide introduced social-distancing policies, with more than half of the world's population on lock-down (Kirby et al., 2021). Specifically, strict quarantine policies aimed at restricting public movement and gatherings had been implemented worldwide. Countless individuals have suffered from the impact of coronavirus disease (COVID-19) on their mental health and well-being. Social media use (SMU), representing online electronic forums used for interacting with others, such as Facebook, Instagram, Twitter, and TikTok, had already become an enormously prevalent tool for social interaction and identity presentation in contemporary society.

Because of the quarantine policies, individuals unprecedentedly relied on social media to connect with family and friends, enhance social support, and receive the latest updates about the pandemic (Zhao & Zhou, 2020). In addition, it is crucial to pay attention to young adults, who are the most frequent users of social media. Berryman et al. (2017) pointed out that SMU has become an essential element of their development process for interacting with peers and forming their identities. Due to the increasing access to social media among young adults during the pandemic, some scholars have expressed concern about potential adverse effects (Masciantonio et al., 2021; Zhao & Zhou, 2020; Boer et al., 2021). Would the pandemic impact young adults' social media use? Were groups of young adults likely to use social media in a more or less harmful way? What motivations drove their social media use during the pandemic? And could certain type of social media influence young adults' mental health? This study addresses these questions in a medium-sized sample of young adults.

The Pandemic and SMU Addiction, Intensity, SMU Motives

Based on the above questions, the first aim of the present study is to investigate whether and how the pandemic changed young adults' SMUs. We will examine SMU here by splitting SMU into three dimensions: SMU intensity, SMU motivation, and SMU addiction. During the pandemic, many countries applied quarantine policies to avoid spreading the virus. For example, most US schools asked their students to prevent in-person interactions and stay at home or in dormitories to take online courses beginning in March 2020. On this account, many young adults were limited to what they could do in their homes or dorm rooms, which could vastly increase their reliance on social media to get connections with others. However, despite the positive aspects of social media use (SMU) during the pandemic, numerous studies have shown that SMU, especially disaster-relevant media exposure, may evoke lower mental health status. For example, people who were once exposed to 9/11 and Iraq War television reported higher levels of post-traumatic stress (PTS) symptoms. Meanwhile, Zhao & Zhou (2020) pointed out that disaster-related SMU was significantly related to mental health problems, such as depressive symptoms, PTSD, and anxiety disorders. Thus, our first goal is to investigate the pandemic's influence on young adults' SMU intensity and SMU addiction and to explore their SMU motivation.

The second aim of the present study is to investigate the relationship between SMU and psychological outcomes among young adults. We distinguished SMU types, SMU intensity, and SMU addiction problems as three separate dimensions of SMU. Specifically, SMU intensity relates to how often people use social media. In contrast, SMU addiction problems indicate additional symptoms while using social media, such as losing control over SMU or neglecting other activities or hobbies as a result of SMU (Boer et al., 2021). Although young adults with

SMU addiction tend to have high SMU intensity, high SMU intensity does not always suggest loss of control over SMU or interference with other aspects of daily life. In other words, young adults who engage in high SMU intensity may be able to control their SMU and balance it with a healthy lifestyle (Masciantonio et al., 2021). On the other hand, young adults with low mental health may not increase their SMU intensity. Many young adults utilize social media extensively to maintain and strengthen their social engagement with peers (Boer et al., 2021).

Existing research suggests that both SMU intensity and SMU addiction problems are negatively associated with young adults' mental health and well-being (Boer et al., 2021; Twenge, Martin, & Campbel, 2018). It is possible that SMU types could positively or negatively relate to young adults' psychological outcomes depending on the motivations underlying their SMU (Masciantonio et al., 2021). Given that these three SMU separate dimensions differ conceptually, they could have differential associations with psychological outcomes. In the following paragraphs, I will sequentially and theoretically elaborate on the relationships between SMU types and psychological outcomes, SMU addiction and psychological outcomes, and potential motivation effects.

Unfortunately, we know little about the directionality of these associations and the underlying mechanisms. Thus, the second aim of this study will address these gaps by investigating bidirectional associations between three dimensions of SMU and psychological outcomes, including well-being, mental health, and perceived stress, by managing motivation as potential moderators of these associations. As a result, this study intends to advance current information about the potential association between SMU behaviors and mental health, which is crucial considering the prominent role that social media plays in young adults' daily lives.

SMU Type and Mental Health, Well-Being

The term “Social Media” is frequently used as an over-general term that ignores the variation between different types. Few studies investigated the specific effects of different social media types on young adults’ well-being and mental health. Pittman and Reich (2016) indicated that using image-based platforms, such as Instagram, TikTok, and Snapchat, was positively correlated with well-being and negatively with loneliness. However, neither such positive nor negative associations appear on text-based platforms like Twitter. Furthermore, Masciantonio et al. (2021) demonstrated that the passive usage of Facebook was negatively related to well-being, mediated by social comparison; active use of Instagram was positively associated with life satisfaction but also harmed mental health, mediated by social support; the active usage of Twitter was associated with higher life satisfaction mediated by social comparison, but the passive use with upward social comparison was negatively correlated with general psychological outcomes. Thus, the above results demonstrate that in looking at the relations between SMU and well-being, it is essential to take into account both the nature of the platforms that are being used and the reasons why they are being used. We need to take the differences among SMU types into account to investigate how SMUs impact young adults’ psychological outcomes accurately.

SMU Intensity and Mental Health, Well Being and Perceived Stress

SMU intensity may not be associated with mental health, but its impact could be different under the pandemic conditions. Several cross-sectional studies suggested that adolescents’ SMU intensity is associated with lower life satisfaction and more depressive symptoms, although there were small associations between SMU intensity and these psychological outcomes (Twenge, Martin, & Campbel, 2018a; Boer et al., 2021). For example, Twenge et al. (2018a) pointed out that only if young adults are low in in-person social interactions and those high in SMU reported significantly increased levels of depressive symptoms. This implies that pre-pandemic reliance on social media use did not seem to serve as a good substitute for actual interactions and that these effects were likely to do to individual differences in sociality.

Nevertheless, SMU intensity may directly lead to less in-person social interaction due to quarantine conditions, under which in-person social interaction is severely limited. It remains an open question as to whether SMU can serve as a viable alternative which is less influenced by individual differences in personality or mental health status. Studies indicated that the associations between SMU intensity and mental health could be bidirectional: adolescents who spend much time on social media may be more vulnerable to mental health issues because they spend less time on face-to-face activities that are crucial for their mental health (Underwood & Ehrenreich, 2017). On the other hand, adolescents with more mental health problems may be more likely to use social media to seek emotional and social support for their problems (Radovic, Gmelin, Stein, & Miller, 2017). We assume this bidirectional association could be strengthened during the pandemic.

However, other research indicated non-significant bidirectional associations between SMU intensity and mental health. Results suggested that SMU intensity was not or only weakly related to lower mental health in some other studies that placed young adults' SMU intensity and SMU addiction problems with mental health in one model (Van den Eijnden, Koning, Doornwaard, Van Gurp, & Ter Bogt, 2018; Boer et al., 2022), which implies that previously observed negative associations between SMU intensity and mental health may be attributed to a confounding influence of SMU addiction problems.

Thus, these assumptions and findings hang over the impacts of SMU intensity on mental health, especially during the pandemic.

SMU Addiction Problems and Mental Health, Well Being, and Perceived Stress

As mentioned above, many studies have shown that more serious SMU addiction problems are related to more mental health problems, such as anxiety disorder, depressive symptoms, and other emotional problems (Shensa et al., 2015; Zhao & Zhou, 2020). Therefore, using SMU addiction to predict mental health may not be that noteworthy. Instead, we plan to compare whether people who are high vs. low on SMU addiction show different patterns of SMU and whether those different patterns are associated with better or poorer mental health. Compared with young adults who merely intensively use social media, those with SMU addiction problems could more easily have mental health issues. More specifically, young adults with higher SMU addiction may have more diminished ability to control their impulses; in other words, they are less likely to control their emotions, thoughts, and behaviors, allowing social media to dominate their lives. Then, young adults could be harmed by this loss of agency, which may easily lead to mental health problems. Overall, an essential thing we want to investigate is whether specific patterns of SMU for particular purposes are supportive of mental health while other patterns are more debilitative.

Mediating Process

The proposed bidirectional pathways between SMU and mental health, well-being, and perceived stress may be driven by several underlying motivations, such as romance, social activity, and social connectedness. However, the corresponding detailed associations haven't received enough empirical attention (Kardefelt-Winther, 2014). To gain a better understanding of how SMU is related to mental health and well-being, numerous studies have suggested taking the potential intermediate variables into account. For example, Blau (2011) indicated that young adults with SMU problems might engage in high levels of self-disclosure on social media.

Meanwhile, Pera (2018) demonstrated that adolescents with SMU problems may perceive their peers' appearance as better than their own, leading to upward social comparison on social media. Based on the Uses and Gratification theory, users actively choose a specific media type to meet their needs. Specifically, people make choices based on their evaluations of how their demands can be met. Then, gratifications obtained through a particular medium can lead to positive attitudes, influencing people's behaviors and continued usage (Shen & Wang, 2019).

MP-Motivation and SMU Intensity

Even though research stated small associations between SMU intensity and mental health, previous studies have established the relationship between motivation and excessive SMU intensity (Lee et al., 2014; Park, 2003). For instance, Park (2003) found that phone usage dependence significantly correlated with motivation variables such as loneliness, killing time, and escapism. Additionally, users may use media to cope with social and interpersonal stress, which could generate SMU dependence and increase SMU intensity as well (Shen & Wang, 2019). Such SMU intentions could be generalized into larger motivation categories like entertainment, social connection, and support. Meanwhile, based on the above findings, I assume that people tend to become more heavily reliant on phones to fulfill their inner needs.

MP-Motivation and SMU Type

Different types of social media can differ in how readily they can satisfy various user needs and motivations (Buzeta et al., 2020). In other words, users tend to use particular platforms that best match their needs. For example, individuals use Facebook mainly for seeking social support and self-presentation; Instagram allows users to satisfy the needs of self-documentation, self-promotion, and see what others are doing; Twitter is primarily used for informational needs (Masciantonio et al., 2021). Meanwhile, after individuals use social media to fulfill their needs, there exist different corresponding feelings and effects on their mental health and well-being. Based on the Uses and Gratifications (U&G) perspective, when people are motivated by killing time, and the types of social media they use are passive and primarily for entertainment purposes, they tend to have a reduced sense of meaningfulness (Cho et al., 2021). Thus, Masciantonio et al. (2021) demonstrated the critical role of motivation as a mediator between different types of social media use and well-being. More specifically, passively using Facebook was negatively associated with well-being, mediated by upward social comparison. In other words, when people keep browsing Facebook, they are inclined to compare themselves with people they perceive to be superior, which could harm their mental health. For example, they may compare profiles, posted photos, or interactions with friends and consider themselves not as distinctive as others. I will be detailing what has been observed from previous studies about these relations below.

Moreover, well-being was negatively correlated with social comparison, whereas Instagram and LinkedIn increased social comparison and Twitter decreased it (Chae, 2018). However, Masciantonio et al. (2021) held the opposite conclusion: there was no relationship between Instagram usage and upward social comparison, which generally makes how different types of social media influence well-being and mental health inconclusive. Thus, it is meaningful to see how different types of social media with various functionalities influence young adults' psychological outcomes, mediated by young adults' motivations.

MP-Motivation and Addiction

Kardefelt-Winther (2014) and Marino et al. (2018) stated that SMU problems can be better understood as "a coping strategy grounded in understandable, but not always healthy" motivations. Furthermore, understanding SMU problems are more about learning and the interaction between the individuals, cultures, and environment instead of merely focusing on casual factors (Wood, 2008). For example, social comparison is a typical SMU motivation among young adults, while increased social comparison could lead to mental health problems (Boer et al., 2021). Young adults with addiction problems related to social media often assign an excessive value to their online presence, leading them to mistakenly perceive the virtual world as a representation of social reality, characterized by idealistic self-presentations. Consequently, they may struggle to reconcile the over-glorified depictions of others with their actual lives, resulting in a gradual inclination towards upward social comparisons. (Boer et al., 2021). More specifically, young adults may perceive their peers' figures, appearance, and abilities as superior to their own, making it easier to feel anxious and lower self-esteem and body evaluations (Faelens et al., 2021).

Meanwhile, SMU problems would lead to decreased motivation, which may reduce mental health. For instance, young adults with SMU addiction problems often treat SMU as one of the essential activities in their daily life, such that abstaining from it could cause anxiety and stress. Thus, they may engage in SMU instead of face-to-face social activities with family and friends, which in the long run may come at the expense of offline contacts and academic accomplishment (Salmela-Aro et al., 2017). Thus, we anticipated first utilizing SMU addiction measures as a marker to problematic SMU. Then, I assume that different patterns of motivations, distinct from those associated with non-problematic SMU, may be associated with problematic SMU. These patterns of motivation, then might be associated with reduced mental health and well-being ,and increased perceived stress.

It should be noted that such relations are likely bidirectional, with problematic usage patterns undermining mental health but also with mental health issues leading to problematic usage. More specifically, young adults with poorer mental health may have negative self-perceptions after being exposed to their peers' idealized appearances on social media, which may reinforce their social comparison with others (Boer et al., 2021). Meanwhile, young adults with poorer mental health and well-being may have less face-to-face interaction with their peers because peers may consider them less appealing as potential friends (Connolly et al., 1992). Thus, in order to compensate and find relief for these motivations, which may stem from either poor mental health or perceived stress, young adults may become more dependent upon and preoccupied with SMU.

Additionally, the Compensatory Internet Use theory suggests that individuals with low psychological well-being may depend on SMU to alleviate their negative emotions and cope with life problems, which in turn implies that they were more likely to use social media based on particular motivations (Kardefelt-Winther, 2014). Meanwhile, Caplan et al. (2009) empirically indicated that the motivations of escapism and achievement mediate the relationship between well-being and online entertainment. On this account, I wanted to take a careful, in-depth look at how college students have been using social media during the pandemic, and I wanted to explore whether certain patterns of usage, with certain motivations, are differentially associated with poorer or better mental health.

Current Study

Using the longitudinal data representing two time periods (T1 and T2) during the pandemic outbreak among US young adults, the present study will examine the impact of the pandemic on SMU and the bidirectional associations between young adults' SMU types and SMU intensity, as well as SMU addiction and psychological outcomes. We will focus on mental health, well-being, and perceived stress as representative variables of psychological outcomes. Drawing on the literature reviewed above, we hypothesized:

H_{1a}: Considering at T1, most students were required to quarantine at home, so they were more likely to get connected through social media than in T2 when schools resumed in-person classes. Thus, I propose that young adults would report higher SMU intensity during the first time period than at the second time period.

H_{1b}: Young adults' responses would indicate more severe SMU addiction problems at the second time period than the first timestamp.

H_{2a}: We predicted that young adults who are high vs. low on SMU addiction show different patterns of SMU, and those different patterns are associated with better or poorer mental health. We did not advance specific predictions for specific SMU patterns but examined their relations in a more exploratory way. We expect the SMU patterns positively associated with SMU addiction to be associated with poorer mental health, whereas those associated with low SMU addiction would be associated with better mental health.

H_{2b}: We also predicted that SMU intensity would be unrelated to mental health, physical health, well-being, and perceived stress.

H_{2c}: We hypothesized that well-being and mental health should point in the opposite direction of perceived stress. Meanwhile, SMU Addition problems would be associated with increased perceived stress and reduced well-being and mental health.

H_3: Finally, we expected to explore if particular motivations mediated the hypothesized associations.

Methods

Participants and Procedure

Participants were recruited from a large private university in the Central United States, beginning in the middle of November and ending in early December 2021. Students participated in the study to earn course credit. The sample was comprised of undergraduate students with a mean age of 21. The final sample was 244 participants, with 67 males and 137 females.

The survey in this study was 53 pages long and was approved by the Vanderbilt Institutional Review Board. Participants first read a brief description of the study and indicated their consent to participate before being presented with the survey.

The survey took approximately 60 minutes to complete. Participants were first asked to recall what they were doing and what they were like during September 2020 (during the Fall semester a year ago from when they answered the questions). They were first asked some questions about where and how they took classes. Then, they were asked about SMU intensity, SMU motivations, SMU addictions, well-being, mental health, and perceived stress respectively. All the participants complete the measures in the same order. After they finished the first part of the survey, they were led to focus on the past month of the time they answered the survey, which was October or November 2021. Then, they answered the same group of questions. At the end of the study, participants answered a series of demographic questions.

Measures

SMU Intensity and SMU types. We designed a scale to measure SMU intensity. We estimate this by asking for both the total amount of time social media of all types were used eacg day, and the frequency with which each individual social media type was used. The part measuring how much time per day, overall, was spent using social media was rated on a single 13-point scale, ranging from 0 “less than 1 hour” to 12 “more than 12 hours”. The part measuring the frequency of use on a specific platform is a 22-item scale, with each item representing a different platform.

Each of these items was rated on a 7-point Likert-type scale ranging from 0 *I didn't use this platform* to 6 I used this platform *5 or more times a day*. Example items include:" Facebook," "Twitter," "YouTube," "LinkedIn," and "Instagram." We added up all the 1's to calculate the total score for each participant as SMU intensity score for further analysis.

SMU Motivation and SMU types. Participants' motivation for using social media was assessed using a modified and expanded version of the Scale of Motives for Using Social Networking Sites (SMU-SNS) that included 18 items (Pertegal et al., 2019). All items were on a 5-point Likert-type scale anchored by 1 *Not at all* to 5 *A great deal*. A sample item is "To get encouragement and support from others." The expanded part of the modified scale contains a follow-up question to ask participants to indicate which platforms they used for each purpose. The same set of platforms as were used in the previous measure were used here.

SMU Addiction Problem. The 8-item Social Media Addiction Questionnaire (SMAQ) was used to measure the intensity of addiction levels using social media (Hawi & Samaha, 2016). SMAQ, stemming from the Facebook intrusion Questionnaire ($\alpha = .78$) and includes behavioral addiction symptoms. All items were on a 5-point Likert-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) and summed to indicate higher levels of addiction. Sample items include "The thought of not being able to access social media made me feel distressed," "I lost track of how much I was using social media," and "I felt connected to others when I used social media."

Well-being. The 9-item Positive Affect & well-Being scale (NIH Toolbox, 2020; Salsman et al., 2014) was used to measure participants' life satisfaction and an overall sense of purpose. All items were on a 5-point Likert-type scale ranging from 1 (*never*) to 5 (*always*). Sample items include "I had a sense of well-being," "I felt hopeful," and "My life was satisfying."

Mental and Physical Health. Mental and physical health was measured and elicited from the 10-item PROMIS Global Health Short Form (NIH Toolbox). This measure is generally scored as separate 4-item subscales for physical and mental health (Kirby et al., 2021). This led to 2 four-item scales for physical health ($\alpha = .74$) and mental health ($\alpha = .70$). The sample items include "In general, how would you rate your mental health, including your mood and ability to think?" and "How would you rate your satisfaction with your social activities and relationships?". These items are on a 5-point Likert scale anchored by 1 *Excellent* and 5 *Poor*, which is in the direction of decreasing physical and mental health.

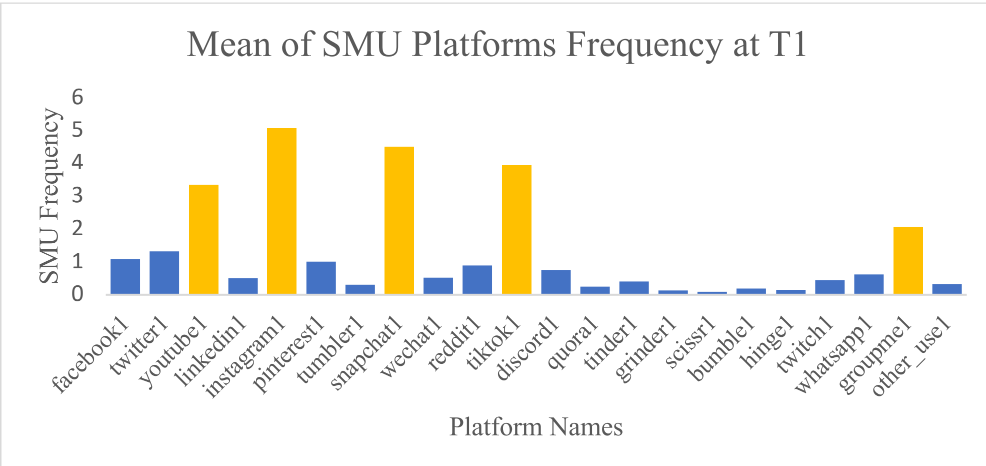
Perceived Stress. The 10-item Perceived Stress Scale (Cohen et al., 1983, $\alpha = .81$) measures how individuals' current circumstances are appraised as stressful (Kirby et al., 2021). We changed the time frame from the last month to the past week. All items were on a 5 Likert-type scale ranging from 1 *never* to 5 *very often*, which is in the direction of increased stress. Sample items include "How often have you been upset because of something that happened unexpectedly?" and "How often have you felt nervous or "stressed"?".

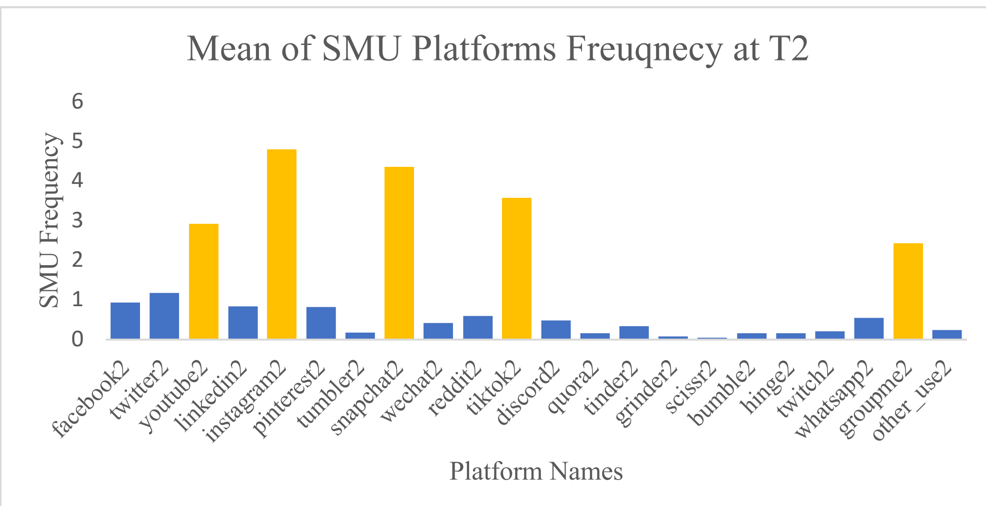
Demographics. We asked students about their Age (1 *under 17* to 7 *Above 21*), Gender (1 *male*, 2 *female*, and *Others*), Country, ethnic or racial background, and home (*city*, *state*, and *country*).

Preliminary Analyses

Data Reduction

We conducted a comprehensive collection of SMU (Social Media Use) data from a total of 22 social media platforms that are commonly used by young adults on a daily basis. After analyzing the SMU intensity table presented below, it was evident that five of the platforms were used much more frequently than the others. To streamline our analysis, we chose to concentrate on the most frequently used social media platforms. Therefore, we carefully selected the top 5 social media platforms based on young adults' social media usage frequency in both T1 and T2. Our study narrowed down to the following five platforms: Instagram, Snapchat, TikTok, YouTube, and GroupMe.





In order to reduce the 18 SMU motivations into a more parsimonious set, I examined the structure of the interrelations among the motivations, across the five retained platforms at both T1 and T2 using three analytic techniques — cluster analysis, factor analysis, and principle components analysis. Although the different techniques yielded slightly different patterns of results from each other, and across the two time-periods, based on observing the commonalities in the results across both methods and time period, and considering what made conceptual sense, I were able to combine the 18 motivations into 6 motivation scales that were retained for further analysis. After careful analysis, we have finalized a set of six motivation variables that will be used for further analysis: Academic, Activity, Romance, Social Connection, Social Activity, and Relaxation. The Academic variable represents the academic purpose, while the Activity variable comprises of the subcategories Do, Eat, Wear, and Buy. The Romance variable includes both Romance and Hookup, whereas the Social Connection variable encompasses Family, Friend, and Meet. The Social Activity variable is composed of Stay Informed, Support, Opinion, Comments, Forget, and Compare, while the Relaxation variable includes Relax and Entertain.

Following a thorough analysis of the intercorrelations among the outcome variables, we were able to condense the outcomes to four variables. To facilitate this, I reverse-coded Perceived Stress, Fatigue, Global Health, Mental Health, Happiness, and Physical Health in advance, ensuring that the scores all pointed in the direction of increasing health. Consequently, we combined Happiness, Well-being, Mental Health, and Perceived Stress into a single variable named *Full Mental Health* ($\alpha = .61$). Additionally, we merged Global Health and Physical Health into a single variable named *Full Physical Health* ($\alpha = .66$). Based on the analysis results, we decided to retain Pain and Fatigue as separate single-item measures.

Item Reliability Statistics

	If item dropped
	Cronbach's α
z_Full_Mental_Health_1	0.608
z_Full_Physical_health	0.664
z_Pain_1	0.742
z_fatigue_1	0.749

Results

H_{1a}

We first hypothesized that young adults would report significantly higher SMU intensity at the first time-period. I conducted paired samples t tests based on the two time periods of the COVID-19 pandemic as the independent variable, with SMU intensity as the dependent variable. The paired samples *t* test on SMU intensity of the top 5 social media platforms in total revealed that SMU intensity at T1 ($M = 4.23$, $SD = 2.45$) was significantly greater than the SMU intensity at T2 ($M = 3.10$, $SD = 1.86$), $t(104) = 5.89$, $p < .001$, $d = .58$, 95% CI [0.37, 0.78].

Specifically, the paired samples *t* test on SMU intensity of YouTube revealed that SMU intensity at T1 ($M = 3.35$, $SD = 2.03$) was significantly greater than the SMU intensity at T2 ($M = 2.92$, $SD = 2.02$), $t(216) = 5.16$, $p < .001$, $d = .35$, 95% CI [0.21, 0.49]. A paired samples t-test conducted on the SMU intensity of Instagram indicated that the SMU intensity during T1 ($M = 5.06$, $SD = 1.53$) was considerably higher than that during T2 ($M = 4.79$, $SD = 1.65$), $t(220) = 2.74$, $p = .003$, $d = .18$, 95% CI [0.05, 0.32]. According to the results of a paired samples t-test on the SMU intensity of TikTok, the SMU intensity was significantly higher during T1 ($M = 3.92$, $SD = 2.56$) compared to that during T2 ($M = 3.57$, $SD = 2.48$), $t(219) = 2.59$, $p = .005$, $d = .18$, 95% CI [0.04, 0.31]. As observed, the overall effect was mirrored in YouTube, Instagram, and TikTok, exhibiting a similar difference.

The findings on Snapchat usage reveal interesting insights into the social media usage of young adults. Unlike other platforms, Snapchat's SMU intensity remained consistent at T1 (M = 4.52, SD = 2.22) and T2 (M = 4.39, SD = 2.17), with no significant increase observed, t(218) = 1.07, p = .142, d = .07. This suggests that Snapchat is a popular platform among young adults, and its usage remains consistent over time. On the other hand, GroupMe showed a significant difference in SMU intensity between T1 (M = 2.05, SD = 1.94) and T2 (M = 2.43, SD = 2.04), t(219) = -2.80, p = .003, d = -.19. However, it is important to note that the usage pattern of GroupMe was different from other social media platforms. The results indicated that young adults used GroupMe more frequently to participate in extracurricular activities when the school resumed in-person classes. This finding highlights the importance of context-specific social media usage among young adults.

Therefore, I concluded that my H_{1a} hypothesis was partially confirmed, as the majority of the platforms supported my hypothesis. However, it is important to acknowledge the exceptions and the nuances in the data, which suggests that social media usage during the pandemic may not be a universal trend and may vary across platforms.

H_{1b}

We hypothesized that the sudden and repetitive increase in SMU during the pandemic may lead to an increase in SMU addiction among young adults at T2 compared to T1, due to long-term exposure to this behavior. However, the paired samples t-test showed that SMU addiction at T1 (M = 1.58, SD = 0.31) was not significantly lower than that at T2 (M = 1.61, SD

= 0.47), $t(15) = -0.21$, $p = 0.42$, $d = -0.05$, 95% CI [-0.54, 0.44]. On this account, this hypothesis was not confirmed. However, I speculated that based on a close examination of the items on the SMAQ, although some items (i.e., “I often thought about social media when I was not using it,” “I often used social media for no particular reason”) reflect problematic, potentially addictive behavior, others (i.e., “I felt connected to others when I used social media,” “I was unable to reduce my social media use”), at least in the context of the isolation of being under quarantine, could simply reflect the predicted situation-driven SMU produced by the early Pandemic. Thus, although I haven’t demonstrated it, it is still possible that the actual problematic SMU was somewhat higher at T2 than at T1. I have listed all the items of the SMAQ in Appendix A for further reference.

H_{2a}

Our second hypothesis stated that young adults with high levels of SMU addiction would display different SMU patterns compared to those with low SMU addiction, and that these patterns would be associated with their mental health status. We predicted that the SMU patterns associated with high SMU addiction would be linked to poorer mental health outcomes, while patterns associated with low SMU addiction would be associated with better mental health outcomes. To test this hypothesis, we first conducted a mean split to classify individuals into high and low addiction groups. We then performed a 2 x 5 repeated measures ANOVA to examine the effect of high vs. low SMU addiction on usage patterns of five different social media platforms (Snapchat, YouTube, TikTok, Instagram, and GroupMe) at two separate time points. This analysis allowed us to investigate how SMU addiction is related to social media usage patterns and how it may impact mental health differently among individuals with high and low levels of addiction. At T1, the ANOVA revealed slight significant differences in SMU patterns between low and high SMU addiction groups, $F\ (4, 412) = 2.69$, $p < .05$, $\eta_p2 = .025$. These analyses yielded noteworthy results in relation to addiction, with main effects being observed whereby the means were generally higher for participants with high addiction compared to those with low addiction. Additionally, a main effect was detected for platform usage patterns, indicating that usage levels varied across the different platforms during the two time periods under investigation. However, the primary focus of this investigation centered on the interaction effect. The findings suggest that elevated levels of addiction were generally linked to increased usage across the various platforms, with the exception of GroupMe, where usage levels were similarly low for both high and low-addiction groups.

Repeated Measures ANOVA T1

Within Subjects Effects

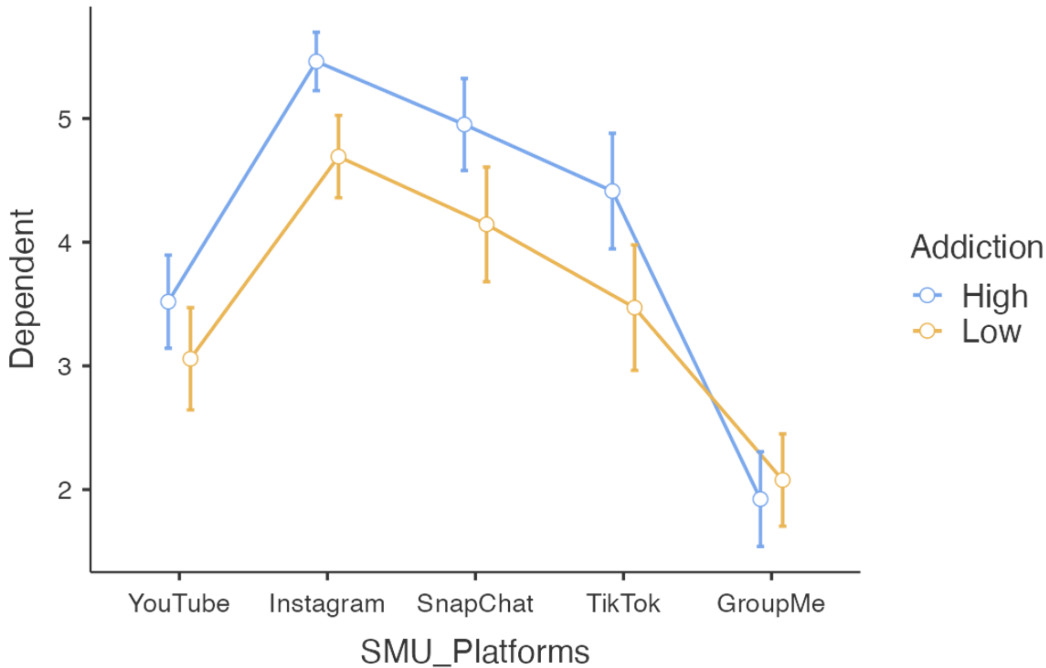
	Sum of Squares	df	Mean Square	F	p	η^2_G	η^2	η^2_p
Addiction	83.1	1	83.11	13.44	<.001	0.019	0.015	0.115
Residual	636.9	103	6.18					
SMU_Platforms	1187.2	4	296.81	78.21	<.001	0.215	0.210	0.432
Residual	1563.6	412	3.80					
Addiction ✻ SMU_Platforms	40.1	4	10.02	2.69	0.031	0.009	0.007	0.025
Residual	1533.9	412	3.72					

Note. Type 3 Sums of Squares

[3]

Estimated Marginal Means at T1

SMU_Platforms ✻ Addiction



The ANOVA at T2 revealed a nonsignificant difference between SMU patterns as a function of SMU addiction, F (4, 404) = 1.83, p = 0.123, $\eta_p 2$ = .018. As with Times, higher addiction at T2 was associated with greater SMU.

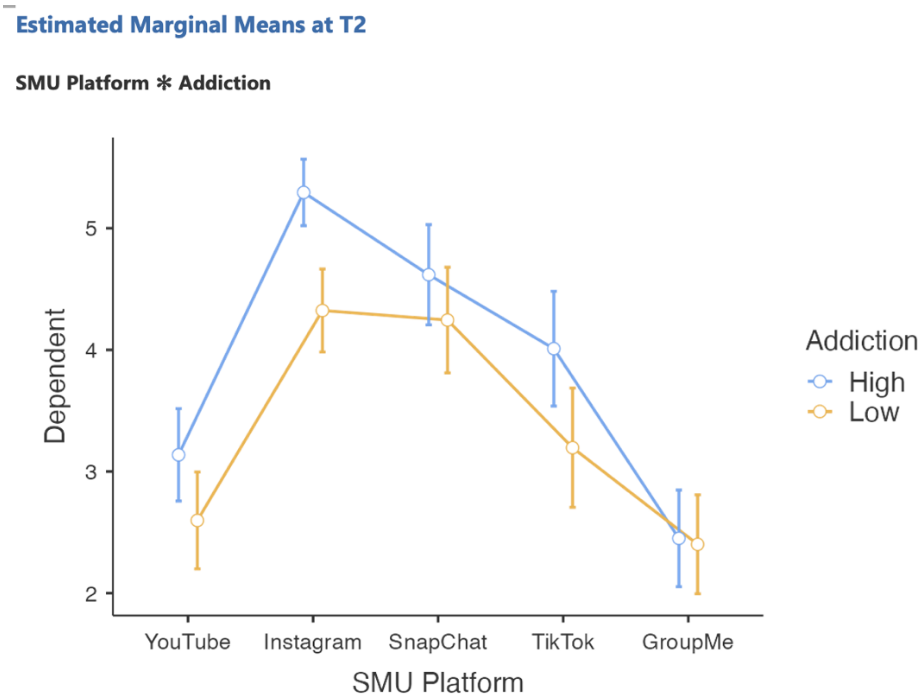
Repeated Measures ANOVA at T2

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_G	η^2	η^2_p
Addiction	76.9	1	76.86	12.57	<.001	0.018	0.015	0.111
Residual	617.5	101	6.11					
SMU Platform	828.7	4	207.17	53.81	<.001	0.162	0.159	0.348
Residual	1555.5	404	3.85					
Addiction ✻ SMU Platform	27.0	4	6.75	1.83	0.123	0.006	0.005	0.018
Residual	1491.6	404	3.69					

Note. Type 3 Sums of Squares

[3]



Furthermore, paired samples t-tests were conducted to understand whether mental health levels differed for individuals who were high or low on SMU addiction. Results from the t-test conducted at T1 revealed significant differences in mental health outcomes between individuals with high social media addiction (M = -0.31, SD = 0.73) and those with low social media addiction (M = .33, SD = .85), $t(105) = 5.66$, $p < .001$, d = .55, 95% CI [0.34, 0.75]. Comparable outcomes were also identified for physical health at Time 1, with significant differences noted between individuals displaying high levels of social media addiction (M = -.30, SD = .95), and those with low levels of social media addiction (M = .31, SD = .98),), $t(105) = 4.58$, $p < .001$, d

= .45, 95% CI [0.24, 0.64].

Paired Samples T-Test at T1

Paired Samples T-Test

			statistic	df	p	Mean difference	SE difference	95% Confidence Interval Lower	95% Confidence Interval Upper		Effect Size	95% Confidence Interval Lower	95% Confidence Interval Upper
Mental_Health_L1	Mental_Health_H1	Student's t	5.66	105	<.001	0.639	0.113	0.452	Inf	Cohen's d	0.550	0.344	0.753
Physical_Health_L1	Physical_health_H1	Student's t	4.58	105	<.001	0.599	0.131	0.382	Inf	Cohen's d	0.445	0.244	0.643

Note. H_a $\mu_{\text{Measure 1 - Measure 2}} > 0$

Descriptives

	N	Mean	Median	SD	SE
Mental_Health_L1	106	0.332	0.240	0.845	0.0821
Mental_Health_H1	106	−0.307	−0.318	0.730	0.0709
Physical_Health_L1	106	0.305	0.359	0.984	0.0955
Physical_health_H1	106	−0.295	−0.218	0.947	0.0920

The results of the paired-sample t-tests conducted at Time 2 were consistent with those observed at Time 1. Specifically, the t-tests revealed significant differences in mental health outcomes between individuals displaying high social media addiction (*M* = -0.25, *SD* = 0.96) and those with low social media addiction (*M* = 0.27, *SD* = 0.98), *t*(107) = 3.79, *p* < .001, *d* = 0.37, 95% CI [0.17, 0.56]. Additionally, comparable outcomes were identified for physical health at Time 2, with significant differences noted between individuals exhibiting high levels of social media addiction (*M* = -0.22, *SD* = 0.92) and those with low levels of social media addiction (*M* = 0.25, *SD* = 0.99), *t*(107) = 3.45, *p* < .001, *d* = 0.33, 95% CI [0.14, 0.53].

Paired Samples T-Test at T2

Paired Samples T-Test

			statistic	df	p	Mean difference	SE difference	95% Confidence Interval Lower	95% Confidence Interval Upper		Effect Size	95% Confidence Interval Lower	95% Confidence Interval Upper
Mental_Health_2L	Mental_Health_H2	Student's t	3.79	107	<.001	0.517	0.136	0.247	0.788	Cohen's d	0.365	0.169	0.559
Physical_Health_2L	Physical_Health_H2	Student's t	3.45	107	<.001	0.476	0.138	0.203	0.749	Cohen's d	0.332	0.138	0.525

Descriptives

	N	Mean	Median	SD	SE
Mental_Health_2L	108	0.266	0.513	0.977	0.0940
Mental_Health_H2	108	−0.252	−0.249	0.958	0.0922
Physical_Health_2L	108	0.253	0.338	0.988	0.0951
Physical_Health_H2	108	−0.222	−0.292	0.918	0.0884

Thus, the results obtained from the above paired samples t-tests largely supported the hypothesis put forth, which postulated that young adults exhibiting high levels of social media addiction would demonstrate poorer mental and physical health outcomes than those with low social media addiction. Specifically, the findings revealed significant differences in both mental and physical health outcomes between the high and low addiction groups at Time 1 and Time 2, providing strong support for the hypothesis.

H_{2b}

A correlation analysis was conducted to understand the relationship between SMU intensity and health issues among young adults. The analysis revealed strong negative correlations between SMU intensity and all measured health variables at T1. This meant that when young adults used social media more frequently during the pandemic, it negatively correlated with their mental and physical health, pain, and fatigue. However, the correlation between SMU and health issues decreased, which might be because young adults had more activity options at T2. Overall, the findings suggest that social media use had a negative impact on young adults' health during the pandemic, but this effect diminished when other activity options became available at T2.

Correlation Matrix between SMU and 4 main Health Variables at T1

Correlation Matrix

		soc_media_use_1	z_Full_Mental_Health_1	z_Full_Physical_health	z_fatigue_1	z_Pain_1
soc_media_use_1	Pearson's r	—				
	p-value	—				
z_Full_Mental_Health_1	Pearson's r	−0.368 ***	—			
	p-value	<.001	—			
z_Full_Physical_health	Pearson's r	−0.358 ***	0.645 ***	—		
	p-value	<.001	<.001	—		
z_fatigue_1	Pearson's r	−0.265 **	0.526 ***	0.343 ***	—	
	p-value	0.001	<.001	<.001	—	
z_Pain_1	Pearson's r	−0.332 ***	0.446 ***	0.430 ***	0.253 ***	—
	p-value	<.001	<.001	<.001	<.001	—

Note. * p < .05, ** p < .01, *** p < .001

Correlation Matrix between SMU and 4 main Health Variables at T2

Correlation Matrix

		soc_media_use_2	z_Full_Mentalhealth_2	z_full_physical_health_2	z_fatigue_2	z_pain_2
soc_media_use_2	Pearson's r	—				
	p-value	—				
z_Full_Mentalhealth_2	Pearson's r	−0.220 *	—	0.662 ***		
	p-value	0.014	—	<.001		
z_full_physical_health_2	Pearson's r	−0.197 *		—		
	p-value	0.028		—		
z_fatigue_2	Pearson's r	−0.170	0.513 ***	0.383 ***	—	0.389 ***
	p-value	0.058	<.001	<.001	—	<.001
z_pain_2	Pearson's r	−0.251 **	0.542 ***	0.400 ***		—
	p-value	0.005	<.001	<.001		—

Note. * p < .05, ** p < .01, *** p < .001

The associations between the variables at T2 exhibited a general weakening in magnitude compared to those observed at T1. To ascertain the statistical significance of this difference, I performed tests to compare the dependent correlations between the two-time points. Nevertheless, the results of the test comparing the dependent correlations between T1 and T2 indicated a nonsignificant weakening of the correlations at T2.

H_{2c}

After identifying a negative correlation between SMU addiction and mental health problems, we utilized a multiple linear regression model to further investigate the relationship between increased SMU addiction and the four main health outcomes in young adults. Our hypothesis posited that a decrease in health levels would correspond to an increase in social media use (SMU) addiction. The analysis yielded unexpected findings at T1, wherein Fatigue and Full Mental Health were found to have a significant and negative impact on SMU addiction. Specifically, the results indicated that higher levels of energy and better overall mental health were associated with lower levels of SMU addiction among young adults, $R^2 = .17$, F (2, 213) = 20.7, $p < .001$.

Linear Regression - DV: SMU and IV: Health at T1

Model Fit Measures

Model	R	R²	Adjusted R²	BIC	RMSE	Overall Model Test F	df1	df2	p
1	0.413	0.170	0.154	1394	5.82	10.7	4	209	<.001

Model Coefficients - smaq_sum_1

Predictor	Estimate	SE	t	p
Intercept	24.513	0.403	60.834	<.001
z_fatigue_1	−0.921	0.468	−1.969	0.050
z_Full_Mental_Health_1	−1.785	0.702	−2.542	0.012
z_Full_Physical_health	−0.626	0.538	−1.163	0.246
z_Pain_1	−0.126	0.462	−0.272	0.786

The multiple linear regression model underwent a notable change at T2, with mental health emerging as the only significant and negative factor, as indicated by a model, $R^2 = .17$, F (2, 213) = 20.7, $p < .001$. Therefore, our regression analysis revealed that higher levels of fatigue and poorer full mental health were associated with increased SMU addiction, further supporting the relationship between health outcomes and SMU addiction.

Linear Regression - DV: SMU and IV - Health at T2

Model Fit Measures

Model	R	R²	Adjusted R²	AIC	BIC	RMSE	Overall Model Test F	df1	df2	p
1	0.312	0.0971	0.0800	1402	1423	6.05	5.67	4	211	<.001

Model Coefficients - smaq_sum_2

Predictor	Estimate	SE	t	p
Intercept	21.688	0.416	52.075	<.001
z_fatigue_2	−0.486	0.489	−0.993	0.322
z_pain_2	−0.640	0.523	−1.225	0.222
z_Full_Mentalhealth_2	−1.028	0.772	−1.333	0.184
z_full_physical_health_2	−0.483	0.557	−0.867	0.387

H_3

Our final hypothesis was to explore whether particular SMU motivations led to different patterns of SMU, which may be associated with better or poorer psychological and physiological health. Multiple Linear Regression Analyses and follow-up step-back analyses were conducted for exploration both at T1 and T2. As a first pass, I regressed the outcome on all six motivations summarized across the five platforms for each of the four health outcomes.

To better understand which motivation(s) were significant predictors across all five platforms, I did a follow-up analysis in which I regressed the outcome on the motivations for each of the five platforms. Because I anticipated that the same motivation would tend to be correlated across the platforms, I did a back-ward stepping procedure to address potential collinearity problems and to identify those platforms was contributing to the overall effect most strongly. For these follow-up analyses, I presented the results of the final equation, with just the significant predictors below. Given many equations in play, my following results report only highlighted the statistically significant relations.

First, Social Activity was the main significant and negative factor predicting Full Mental Health within and across the Top 5 social media platforms at T1 (β = -.25, t(224) = -.25, p < .001) and T2 (β = -.20, t(220) = -3.02, p < .005). Social Activity also negatively predicted Full Physical Health at T1 (β = -.15, t(224) = -2.24, p < .05) and T2 (β = -.23, t(220) = -3.47, p < .001). Additionally, Social Activity negatively influenced pain across the Top 5 platforms at T2, β = -.16, t(218) = -2.36, p = .019.

Specifically, young adults using Instagram to pursue social activity at T1 would negatively predict mental health (β = -.01, t(224) = -3.90, p < .001). Whereas these harmful SMU patterns changed at T2, during which YouTube (β = -.19, t(219) = -2.75, p = .006) and TikTok (β

= -.17, $t(219) = -2.53$, $p = .012$) became the main negative factors influencing mental health. Additionally, GroupMe usage for Social Activity at T2 could positively predict mental health, $\beta = .21$, $t(218) = 3.13$, $p = .002$.

The SMU platforms' combination of YouTube ($\beta = -.19$, $t(219) = -2.75$, $p = .006$) and TikTok ($\beta = -.17$, $t(219) = -2.53$, $p = .012$) at T2 also negatively affected Full Physical Health, which did not appear at T1. And simply using YouTube for Social Activity at T2 negatively predicted pain, $\beta = -.02$, $t(218) = -3.47$, $p < .001$.

Compared with Social Activity, using particular social media platforms for Social Connection played a bit more positive effects on promoting mental health at T1. During the pandemic, young adults using Snapchat ($\beta = .15$, $t(222) = 2.08$, $p < .05$) and YouTube ($\beta = .14$, $t(222) = 2.20$, $p < .05$) for Social Connection could positively predict mental health, whereas using Instagram could negatively predict mental health, $\beta = -.18$, $t(222) = -2.37$, $p < .05$. However, such effectiveness did not appear correspondingly at T2.

Then, after repeatedly conducting regression analyses for each platform on all six motivations, it was discovered that Social Connection appeared as the second most frequent significant predictor, influencing four main health factors. When I presented the findings of the follow-up analyses, only statistically significant effects were reported. While this approach is useful for identifying noteworthy results, it raises concerns about the potential for capitalizing on chance. Therefore, the results of these analyses should be considered exploratory and treated with caution.

For Snapchat at T1, besides Social Activity as the negative predictor, young adults' motivation for Social Connection could positively predict mental health, $\beta = -.22$, $t(223) = -3.11$, $p < .005$. This showed that close and healthy relationships were much more effective in facilitating mental health than online social activity. Interestingly, using Snapchat to pursue social connection could even predict less pain at T1, $\beta = .18$, $t(222) = 2.77$, $p = .006$. However, such a significant positive predictor disappeared at T2.

The results for social connection at T1 were particularly interesting, but preliminary. These findings provided evidence that SMU may have mitigated the adverse effects of pandemic quarantines at T1 (but not at T2) through promoting social connections. These results will be discussed in detail in the discussion section, with careful consideration given to their provisional nature.

Discussion

The impact of the COVID-19 pandemic on young adults' social media use (SMU) intensity and addiction, as well as its role in contributing to mental health problems, is a subject of debate in the existing literature. Our study aimed to explore the impacts of the pandemic on SMU intensity and addiction among young adults by measuring two timestamps representing two statuses of the pandemic waves. Furthermore, we examined the associations between SMU and both psychological and physiological health while differentiating SMU into three dimensions: SMU type, SMU intensity, and SMU addiction problems. We also investigated whether specific motivations played as an important factor in the proposed associations with SMU and health inssues.

Our findings showed that young adults clearly more frequently used social media during the early phase of the pandemic, when most were under quarantine than later, when fairly normal class attendance had resumed. In addition, SMU addiction was a significant predictor of poorer mental and physical health. However, the difference in SMU patterns between young adults who were in low and high addiction groups was not obvious. Also, SMU intensity was strongly negatively correlated with mental health, especially at T1. Such strong correlations diminished or disappeared at T2.

It is plausible that the influence of mental health on social media use (SMU) was more prominent than the reverse. Specifically, during the initial phase of the pandemic, the state of quarantine may have elicited unfavorable mental health outcomes, and the young adults in the cohort may have resorted to augmenting their SMU as a coping mechanism to counteract the deleterious effects of the pandemic on their emotional and psychological well-being. However, over time, as mental health improved, the negative correlation between SMU intensity and mental health decreased or ceased. This pattern of results suggests that the relationship between SMU and mental health is complex and dynamic and may be influenced by a range of factors that change over time. Further research is necessary to investigate the potential mechanisms underlying these findings and to better understand the nature of the relationship between SMU and mental health over time.

Finally, our exploration of motivation showed that Social Activity was the main motivating factor that negatively influenced young adults' mental and physical health. Nevertheless, different SMU patterns and motivation combinations had various effects on health issues across two-time stamps, which could be influenced by each social media platform's different functions. Also, even though GroupMe is the fifth most frequently used social media platform among young adults, its main usage is at school for academics and extracurricular activities. That could be why the relevant results for GroupMe were sometimes different than the other four social media platforms. The results of the exploratory analyses revealed that, for specific social media platforms (SnapChat), utilizing it at T1 to enhance social connection with peers and family members demonstrated a positive association with mental health, which was not immediately discernible at T2. These outcomes suggest that certain endeavors to utilize social media as a means of mitigating the adverse effects of the quarantine conditions during the early stages of the pandemic may have yielded positive outcomes. This finding underscores the potential utility of social media as a coping mechanism to foster social connections and support networks, which may have played a pivotal role in maintaining positive mental health outcomes during times of adversity.

The current study has several limitations. First, our measured SMU intensity combines passive and active social media activities. However, studies indicated that disentangling these independent effects was necessary to examine further how SMU intensity influences mental health.

Secondly, for the SMAQ used in H1b, some particular statements could be more easily agreed upon during the pandemic when young adults have to use social media to get connected to the outer world other than be truly addicted to social media. Furthermore, under conditions of the early Pandemic, when there was likely more of a need to reach out via social media to friends and family, some of the statements defining the scale may not have been good markers for problematic usage. Thus, at this point, we are ambiguous about this measure as a measure of actual addiction, at least in this study and under the study conditions. Future studies can consider using other measures to assess SMU addiction.

Further, for H2b, there are several potential explanations for the observed decrease in the correlation between social media use (SMU) and mental and physical health, pain, and fatigue among young adults when in-person classes resumed and students returned to school. One possible explanation is that the resumption of in-person classes provided young adults with greater opportunities for social interaction and engagement, which may have reduced their reliance on social media for social connectedness. Additionally, in-person classes may have offered a more structured routine and increased physical activity, which could have positively impacted mental and physical health outcomes. It is also possible that the increased demands and responsibilities of in-person classes and academic work may have shifted young adults' focus away from social media use, leading to a reduced correlation with negative health outcomes.

For H2c, possible explanations for this change could include the impact of evolving circumstances during the pandemic or other unmeasured factors that may have influenced young adults' health outcomes. For instance, it is possible that as the pandemic progressed, mental health became a more salient concern for young adults, leading to a stronger relationship with SMU addiction. Alternatively, changes in social media use patterns or other confounding factors may have contributed to the observed decrease in the influence of fatigue and full mental health on SMU addiction at T2. Further research is needed to fully understand the factors contributing to these changes over time.

Then, the data we collected for timestamp 1 relied on participants’ retrospective memory, which may lead our results to be biased based on each participant’s memory accuracy. For example, self-report measures of addiction and usage motivation can be limited by factors such as social desirability bias and the participants' level of insight into their own behaviors.

Also, most of our participants were female, which could be an important limitation. Gender differences may play an important role in SMU behaviors, psychological and physiological status, and SMU motivation. Thus, future studies should take gender differences into account when recruiting subjects.

Our study produced numerous significant findings that have practical implications and serve as a potent launching pad for subsequent research. Specifically, we have gained a deeper understanding that specific SMU patterns have a significant impact on health concerns such as Instagram and TikTok usage. Nevertheless, combining multiple measures and approaches is essential to more comprehensively assess social media use and its effects. Researchers can implement open-ended questions in the survey or conduct follow-up interviews to allow participants to share their experiences and perspectives on their social media use during and after the pandemic. This can provide a more in-depth understanding of their behaviors and motivations. Instead of drawing definitive conclusions, it is imperative to explore the motivations underlying social media use beyond the current study's scope, as the exploratory analyses indicate that the reasons behind a person's social media use may significantly impact whether the mental health effects of such use are positive or negative. This calls for more comprehensive investigations utilizing qualitative methods, such as open-ended questions, to gain deeper insight into users' motivations for employing different social media platforms. By employing a more nuanced and comprehensive approach, researchers can potentially gain a deeper understanding of the complex interplay between social media use, its underlying motivations, and mental health outcomes, which can have critical implications for designing interventions to improve individuals' mental health in the context of social media use.

Meanwhile, there is a lack of existing research that investigates the feature-level functions or algorithms of these social media platforms, as well as how the combination of these functions could potentially harm young adults. For example, when people suffering from depression are guided by algorithms that lead to recommendations that only reinforce depressive symptoms. Thus, looking into the future, researchers can focus on more on feature-level investigation accompanied by relevant SMU motivation and addiction assessment, which could be a more targeted way to understand various behavioral and emotional aspects of SMU at a more refined level. We can rely on Ecological Momentary Assessments (EMAs) technologies to track the feature-level uses of selected SMU types based on results from the current study and track the change in young adults' dynamic emotional status based on what specific features they use in social media. Then, we can further understand how SMU results in mental health problems.

By examining the small functions of social media platforms, we can identify how the combination of these features can contribute to negative health outcomes, such as addiction, anxiety, depression, and body image issues. Moreover, conducting feature-level research analyses can help identify potential solutions or interventions that could mitigate these risks. For instance, by understanding how specific features of social media platforms affect users' behaviors, developers can design tools to limit or modify those features to promote healthier usage patterns. Likewise, researchers can use their findings to create educational programs that equip young adults with the knowledge and skills they need to use social media safely and responsibly.

Appendix A

Table 1. The SMAQ Scale Items

Please answer each of the following questions regarding your experiences during the past month.
I often thought about social media when I was not using it. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I often used social media for no particular reason. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I argued with others becaue of my social media use. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I interrupted whatever else I was doing when I felt the need to access social media. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I felt connected to others when I used social media. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I lost track of how much I was using social media. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
The thought of not being able to access social media made me feel distressed. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree
I was unable to reduce my social media use. ◯ strongly disagree ◯ somewhat disagree ◯ neither agree nor disagree ◯ somewhat agree ◯ strongly agree

Appendix B

Table 1. Full Regression Analyses (Motivation vs. 4 Main Health) At T1

Linear Regression_Total_MentalHealth at T1

Model Fit Measures

Model	R	R^2
1	0.293	0.0858

Model Coefficients - z_Full_Mental_Health_1

			95% Confidence Interval				
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate
Intercept	0.12817	0.12671	−0.12155	0.37789	1.0115	0.313	
Total_Activity_1	0.00627	0.00406	−0.00174	0.01427	1.5434	0.124	0.12081
Total_Romance_1	3.05e−4	0.00454	−0.00865	0.00926	0.0671	0.947	0.00461
Total_Social_Connection_1	0.00928	0.00544	−0.00143	0.02000	1.7082	0.089	0.13222
Total_Social_Activity_1	−0.02255	0.00555	−0.03350	−0.01160	−4.0597	<.001	−0.35498
Total_Relaxation_1	−0.00168	0.00262	−0.00683	0.00348	−0.6410	0.522	−0.04870

Linear Regression_Total_PhysicalHealth at T1

Model Fit Measures

Model	R	R^2
1	0.186	0.0347

Model Coefficients - z_Full_Physical_health

			95% Confidence Interval				
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate
Intercept	0.0572	0.15477	−0.24782	0.36224	0.3696	0.712	
Total_Activity_1	−1.10e−4	0.00496	−0.00989	0.00967	−0.0221	0.982	−0.00178
Total_Romance_1	9.74e−4	0.00555	−0.00996	0.01191	0.1755	0.861	0.01238
Total_Social_Connection_1	0.0107	0.00664	−0.00242	0.02374	1.6056	0.110	0.12770
Total_Social_Activity_1	−0.0150	0.00678	−0.02835	−0.00161	−2.2074	0.028	−0.19834
Total_Relaxation_1	−9.90e−4	0.00320	−0.00729	0.00531	−0.3097	0.757	−0.02418

Linear Regression_Total_Fatigue at T1

Model Fit Measures

Model	R	R²
1	0.150	0.0226

Model Coefficients - z_fatigue_1

			95% Confidence Interval				
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate
Intercept	0.22854	0.15742	−0.08171	0.53880	1.452	0.148	
Total_Activity_1	−0.00172	0.00499	−0.01156	0.00812	−0.344	0.731	−0.0279
Total_Romance_1	0.00155	0.00559	−0.00946	0.01255	0.277	0.782	0.0197
Total_Social_Connection_1	−0.00700	0.00668	−0.02017	0.00618	−1.047	0.296	−0.0841
Total_Social_Activity_1	−0.00663	0.00684	−0.02010	0.00685	−0.969	0.333	−0.0877
Total_Relaxation_1	6.22e−4	0.00323	−0.00575	0.00700	0.192	0.848	0.0151

Linear Regression_Total_pain at T1

Model Fit Measures

Model	R	R²
1	0.0980	0.00960

Model Coefficients - z_Pain_1

			95% Confidence Interval				
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate
Intercept	−0.08201	0.15719	−0.39181	0.22780	−0.522	0.602	
Total_Activity_1	0.00178	0.00504	−0.00816	0.01171	0.352	0.725	0.0289
Total_Romance_1	0.00108	0.00581	−0.01037	0.01253	0.186	0.853	0.0134
Total_Social_Connection_1	0.00744	0.00674	−0.00584	0.02072	1.104	0.271	0.0894
Total_Social_Activity_1	−0.00772	0.00691	−0.02133	0.00589	−1.118	0.265	−0.1026
Total_Relaxation_1	4.16e−4	0.00325	−0.00599	0.00682	0.128	0.898	0.0102

Table 2. Full Regression Analyses (Social Activity Across 5 Platforms vs. 4 Main Health) At T1

Linear Regression_Fatigue_SocialActivity_T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.173	0.0298	0.00751	642	666	0.983	1.34	5	218	0.249

Model Coefficients - z_fatigue_1

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.16765	0.10659	1.573	0.117	
Social_Activity_1_YouTube	−0.00646	0.00525	−1.230	0.220	−0.0881
Social_Activity_1_SnapChat	0.00208	0.00392	0.531	0.596	0.0462
Social_Activity_1_Instagram	−0.00220	0.00328	−0.671	0.503	−0.0611
Social_Activity_1_TikTok	−0.00301	0.00424	−0.711	0.478	−0.0603
Social_Activity_1_GroupMe	−0.01182	0.00900	−1.314	0.190	−0.0901

Linear Regression_SocialActivity_total-platforms at T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.262	0.0686	0.0475	560	584	0.810	3.24	5	220	0.008

Model Coefficients - z_Full_Mental_Health_1

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept	0.26788	0.08685	0.09671	0.43905	3.08428	0.002			
Social_Activity_1_Instagram	−0.00606	0.00270	−0.01138	−7.53e−4	−2.25024	0.025	−0.2007	−0.377	−0.0249
Social_Activity_1_YouTube	−0.00335	0.00432	−0.01187	0.00518	−0.77403	0.440	−0.0542	−0.192	0.0838
Social_Activity_1_SnapChat	−1.66e−5	0.00323	−0.00639	0.00636	−0.00512	0.996	−4.36e−4	−0.168	0.1672
Social_Activity_1_TikTok	−0.00228	0.00349	−0.00917	0.00461	−0.65241	0.515	−0.0541	−0.217	0.1092
Social_Activity_1_GroupMe	−0.00161	0.00742	−0.01623	0.01300	−0.21757	0.828	−0.0146	−0.146	0.1173

Linear Regression_Pain_SocialActivity_T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.120	0.0143	−0.00830	645	669	0.991	0.633	5	218	0.675

Model Coefficients - z_Pain_1

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.09275	0.10641	0.8717	0.384	
Social_Activity_1_YouTube	−0.00437	0.00531	−0.8240	0.411	−0.05967
Social_Activity_1_SnapChat	0.00443	0.00398	1.1127	0.267	0.09793
Social_Activity_1_Instagram	−0.00363	0.00330	−1.1009	0.272	−0.10142
Social_Activity_1_TikTok	−2.83e−4	0.00428	−0.0661	0.947	−0.00567
Social_Activity_1_GroupMe	0.00414	0.00908	0.4565	0.648	0.03158

Linear Regression_SocialActivity_total-platforms_physicalhealth at T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.172	0.0297	0.00762	648	671	0.983	1.35	5	220	0.246

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
Social_Activity_1_YouTube	0.672	1	0.672	0.677	0.412
Social_Activity_1_SnapChat	0.155	1	0.155	0.157	0.693
Social_Activity_1_Instagram	0.422	1	0.422	0.425	0.515
Social_Activity_1_TikTok	1.355	1	1.355	1.366	0.244
Social_Activity_1_GroupMe	1.167	1	1.167	1.176	0.279
Residuals	218.323	220	0.992		

Note. Type 3 sum of squares

Table 3. Full Regression Analyses (Social Connection Across 5 Platforms vs. 4 Main Health) At T1

Linear Regression_MentalHealth_SocialConnection_T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.226	0.0510	0.0295	564	588	0.818	2.37	5	220	0.041

Model Coefficients - z_Full_Mental_Health_1

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.02990	0.10875	0.275	0.784	
Social_Connection_1_YouTube	0.01308	0.00599	2.184	0.030	0.1439
Social_Connection_1_SnapChat	0.00518	0.00240	2.153	0.032	0.1626
Social_Connection_1_TikTok	−0.00121	0.00352	−0.345	0.731	−0.0235
Social_Connection_1_Instagram	−0.00490	0.00219	−2.243	0.026	−0.1683
Social_Connection_1_GroupMe	−0.00231	0.00352	−0.656	0.513	−0.0440

Linear Regression_PhysicalHealth_SocialConnection_T1

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.148	0.0219	−2.96e−4	649	673	0.987	0.987	5	220	0.427

Model Coefficients - z_Full_Physical_health

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	−0.07213	0.13124	−0.550	0.583	
Social_Connection_1_YouTube	0.00733	0.00723	1.014	0.311	0.0679
Social_Connection_1_SnapChat	0.00531	0.00290	1.829	0.069	0.1402
Social_Connection_1_TikTok	−0.00329	0.00425	−0.774	0.440	−0.0535
Social_Connection_1_Instagram	−0.00188	0.00264	−0.710	0.478	−0.0541
Social_Connection_1_GroupMe	−0.00305	0.00424	−0.718	0.474	−0.0489

Linear Regression_Fatigue_SocialConnection_T1

Model Fit Measures

							Overall Model Test			
Model	R	R²	Adjusted R²	AIC	BIC	RMSE	F	df1	df2	p
1	0.341	0.116	0.0958	621	645	0.938	5.73	5	218	<.001

Model Coefficients - z_fatigue_1

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.22120	0.12560	1.76111	0.080	
Social_Connection_1_YouTube	6.91e–5	0.00781	0.00886	0.993	5.68e–4
Social_Connection_1_SnapChat	0.00987	0.00278	3.54772	<.001	0.2599
Social_Connection_1_TikTok	–0.00292	0.00404	–0.72200	0.471	–0.0477
Social_Connection_1_Instagram	–0.01268	0.00254	–5.00268	<.001	–0.3654
Social_Connection_1_GroupMe	–0.00120	0.00404	–0.29839	0.766	–0.0194

Linear Regression_Pain_SocialConnection_T1

Model Fit Measures

							Overall Model Test			
Model	R	R²	Adjusted R²	AIC	BIC	RMSE	F	df1	df2	p
1	0.252	0.0633	0.0418	634	658	0.966	2.95	5	218	0.014

Model Coefficients - z_Pain_1

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	–0.12281	0.12847	–0.9560	0.340	
Social_Connection_1_YouTube	–2.00e–4	0.00708	–0.0283	0.977	–0.00186
Social_Connection_1_SnapChat	0.01006	0.00285	3.5249	<.001	0.26625
Social_Connection_1_TikTok	–0.00675	0.00420	–1.6053	0.110	–0.10909
Social_Connection_1_Instagram	–0.00491	0.00259	–1.8929	0.060	–0.14214
Social_Connection_1_GroupMe	0.00303	0.00416	0.7278	0.468	0.04878

Table 4. Full Regression Analyses (Motivation vs. 4 Main Health) At T2

Linear Regression_Total_MentalHealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.243	0.0592	0.0374	552	576	0.813	2.72	5	216	0.021

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
Total_Activity_2	0.2324	1	0.2324	0.3424	0.559
Total_Romance_2	0.4626	1	0.4626	0.6816	0.410
Total_Social_Connection_2	2.5446	1	2.5446	3.7488	0.054
Total_Social_Activity_2	7.6581	1	7.6581	11.2823	<.001
Total_Relaxation_2	0.0141	1	0.0141	0.0208	0.885
Residuals	146.6144	216	0.6788		

Note. Type 3 sum of squares

Linear Regression_Total_PhysicalHealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.284	0.0806	0.0593	624	648	0.957	3.79	5	216	0.003

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
Total_Activity_2	1.503	1	1.503	1.598	0.208
Total_Romance_2	1.393	1	1.393	1.481	0.225
Total_Social_Connection_2	3.567	1	3.567	3.792	0.053
Total_Social_Activity_2	10.186	1	10.186	10.828	0.001
Total_Relaxation_2	0.550	1	0.550	0.584	0.445
Residuals	203.192	216	0.941		

Note. Type 3 sum of squares

Linear Regression_Total_Fatigue_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.223	0.0495	0.0275	632	656	0.973	2.25	5	216	0.050

Model Coefficients - z_fatigue_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.19084	0.14523	1.314	0.190	
Total_Activity_2	0.00243	0.00490	0.496	0.621	0.0377
Total_Romance_2	−0.00664	0.00437	−1.520	0.130	−0.1069
Total_Social_Connection_2	0.01045	0.00627	1.666	0.097	0.1382
Total_Social_Activity_2	−0.00810	0.00694	−1.167	0.244	−0.1004
Total_Relaxation_2	−0.00879	0.00370	−2.378	0.018	−0.1843

Linear Regression_Total_Pain_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.192	0.0367	0.0142	629	653	0.979	1.63	5	214	0.153

Model Coefficients - z_pain_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.01070	0.14742	0.0726	0.942	
Total_Activity_2	−0.00101	0.00497	−0.2033	0.839	−0.0157
Total_Romance_2	−0.00458	0.00440	−1.0405	0.299	−0.0740
Total_Social_Connection_2	0.00510	0.00632	0.8070	0.421	0.0676
Total_Social_Activity_2	−0.01637	0.00702	−2.3313	0.021	−0.2026
Total_Relaxation_2	0.00339	0.00378	0.8970	0.371	0.0702

Table 5. Full Regression Analyses (Social Activity Across 5 Platforms vs. 4 Main Health) At T2

Linear Regression_socialactivity_totalplatforms_mentalhealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.353	0.125	0.104	536	560	0.784	6.15	5	216	<.001

Model Coefficients - z_Full_Mentalhealth_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.17735	0.07805	2.272	0.024	
Social_Activity_2_YouTube	−0.01543	0.00460	−3.352	<.001	−0.2279
Social_Activity_2_SnapChat	−0.00107	0.00339	−0.316	0.752	−0.0255
Social_Activity_2_Instagram	6.31e−4	0.00260	0.243	0.809	0.0211
Social_Activity_2_TikTok	−0.01033	0.00414	−2.495	0.013	−0.2111
Social_Activity_2_GroupMe	0.02084	0.00669	3.115	0.002	0.2067

Linear Regression_socialactivity_totalplatform_physicalhealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.306	0.0934	0.0725	621	645	0.950	4.45	5	216	<.001

Model Coefficients - z_full_physical_health_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.23817	0.09459	2.518	0.013	
Social_Activity_2_YouTube	−0.01684	0.00558	−3.018	0.003	−0.2089
Social_Activity_2_SnapChat	−0.00244	0.00411	−0.593	0.554	−0.0487
Social_Activity_2_Instagram	−7.64e−4	0.00315	−0.242	0.809	−0.0214
Social_Activity_2_TikTok	−0.00853	0.00502	−1.699	0.091	−0.1463
Social_Activity_2_GroupMe	0.01342	0.00811	1.656	0.099	0.1118

Linear Regression_SocialActivity_Fatigue_T2

Model Fit Measures

							Overall Model Test			
Model	R	R²	Adjusted R²	AIC	BIC	RMSE	F	df1	df2	p
1	0.146	0.0214	−0.00120	638	662	0.987	0.947	5	216	0.452

Model Coefficients - z_fatigue_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.10549	0.09828	1.0734	0.284	
Social_Activity_2_YouTube	−0.00395	0.00580	−0.6814	0.496	−0.04900
Social_Activity_2_SnapChat	−0.00322	0.00427	−0.7548	0.451	−0.06446
Social_Activity_2_Instagram	−3.04e−4	0.00327	−0.0929	0.926	−0.00854
Social_Activity_2_TikTok	−0.00438	0.00521	−0.8407	0.401	−0.07521
Social_Activity_2_GroupMe	0.00829	0.00842	0.9838	0.326	0.06902

Linear Regression_SocialActivity_Pain_T2

Model Fit Measures

							Overall Model Test			
Model	R	R²	Adjusted R²	AIC	BIC	RMSE	F	df1	df2	p
1	0.247	0.0612	0.0393	623	647	0.967	2.79	5	214	0.018

Model Coefficients - z_pain_2

Predictor	Estimate	SE	t	p
Intercept	0.18098	0.09656	1.874	0.062
Social_Activity_2_YouTube	−0.01836	0.00568	−3.231	0.001
Social_Activity_2_SnapChat	−0.00325	0.00419	−0.776	0.439
Social_Activity_2_Instagram	−6.02e−4	0.00321	−0.188	0.851
Social_Activity_2_TikTok	−8.41e−4	0.00511	−0.165	0.869
Social_Activity_2_GroupMe	0.00660	0.00826	0.799	0.425

Table 6. Full Regression Analyses (Social Connection Across 5 Platforms vs. 4 Main Health) At T2

Linear Regression_socialconnection_total_mentalhealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.166	0.0276	0.00509	559	583	0.826	1.23	5	216	0.298

Model Coefficients - z_Full_Mentalhealth_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	−0.07126	0.11101	−0.642	0.522	
Social_Connection_2_YouTube	0.00424	0.00685	0.619	0.537	0.0433
Social_Connection_2_SnapChat	6.70e−4	0.00223	0.301	0.764	0.0241
Social_Connection_2_TikTok	−0.00808	0.00355	−2.273	0.024	−0.1686
Social_Connection_2_Instagram	0.00143	0.00198	0.724	0.470	0.0561
Social_Connection_2_GroupMe	0.00390	0.00377	1.034	0.302	0.0701

Linear Regression_socialconnection_total_fatigue_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.107	0.0114	−0.0115	640	664	0.992	0.499	5	216	0.777

Model Coefficients - z_fatigue_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	−0.00912	0.13330	−0.0684	0.946	
Social_Connection_2_YouTube	−0.00463	0.00823	−0.5628	0.574	−0.0397
Social_Connection_2_SnapChat	−0.00307	0.00267	−1.1479	0.252	−0.0927
Social_Connection_2_TikTok	0.00108	0.00427	0.2531	0.800	0.0189
Social_Connection_2_Instagram	0.00288	0.00237	1.2116	0.227	0.0946
Social_Connection_2_GroupMe	−0.00291	0.00452	−0.6434	0.521	−0.0440

Linear Regression_socialconnection_total_physicalhealth_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.123	0.0152	–0.00761	640	663	0.990	0.666	5	216	0.649

Model Coefficients - z_full_physical_health_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	–0.02055	0.13304	–0.154	0.877	
Social_Connection_2_YouTube	0.00454	0.00821	0.553	0.581	0.0389
Social_Connection_2_SnapChat	–0.00261	0.00267	–0.976	0.330	–0.0787
Social_Connection_2_TikTok	–0.00466	0.00426	–1.093	0.276	–0.0816
Social_Connection_2_Instagram	0.00279	0.00237	1.178	0.240	0.0918
Social_Connection_2_GroupMe	0.00128	0.00451	0.283	0.778	0.0193

Linear Regression_socialconnection_total_pain_T2

Model Fit Measures

							Overall Model Test			
Model	R	R^2	Adjusted R^2	AIC	BIC	RMSE	F	df1	df2	p
1	0.177	0.0313	0.00863	630	654	0.982	1.38	5	214	0.233

Model Coefficients - z_pain_2

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.00263	0.13214	0.0199	0.984	
Social_Connection_2_YouTube	0.01437	0.00815	1.7643	0.079	0.1238
Social_Connection_2_SnapChat	–0.00111	0.00267	–0.4171	0.677	–0.0336
Social_Connection_2_TikTok	–0.00882	0.00423	–2.0854	0.038	–0.1551
Social_Connection_2_Instagram	0.00147	0.00236	0.6218	0.535	0.0484
Social_Connection_2_GroupMe	0.00163	0.00448	0.3637	0.716	0.0247

Appendix C

Table 1. Reliability Analysis of SMAQ Scale

Item Reliability Statistics

				if item dropped	
	mean	sd	item-rest correlation	Cronbach's α	McDonald's ω
smaq1_1	2.94	1.17	0.600	0.787	0.790
smaq2_1	3.99	1.07	0.524	0.798	0.800
smaq3_1	1.84	1.17	0.453	0.807	0.811
smaq4_1	2.72	1.35	0.591	0.787	0.792
smaq5_1	3.38	1.10	0.280	0.828	0.829
smaq6_1	3.88	1.16	0.533	0.796	0.799
smaq7_1	2.90	1.38	0.677	0.773	0.777
smaq8_1	2.95	1.26	0.612	0.784	0.788

Table 2. Reliability Analysis of Perceived Stress Scale

Item Reliability Statistics

				if item dropped	
	mean	sd	item-rest correlation	Cronbach's α	McDonald's ω
pss1	3.18	0.955	0.447	0.818	0.820
pss2	3.48	1.025	0.508	0.812	0.814
pss3	3.83	1.003	0.570	0.805	0.807
pss4_r	2.80	0.980	0.473	0.815	0.817
pss5_r	3.18	0.876	0.499	0.813	0.815
pss6	2.91	1.030	0.626	0.799	0.801
pss7_r	2.89	0.933	0.416	0.821	0.822
pss8_r	2.96	0.983	0.533	0.809	0.811
pss9	3.32	1.005	0.444	0.818	0.820
pss10	3.11	1.147	0.606	0.801	0.803

Table 3. Reliability Analysis of PROMIS Mental Health Scale

Item Reliability Statistics

				if item dropped	
	mean	sd	item-rest correlation	Cronbach's α	McDonald's ω
Global_10_(i)_1	3.40	0.999	0.665	0.856	0.858
Global_02_(i)_1	3.15	1.115	0.711	0.837	0.852
Global_04_(i)_1	3.57	1.231	0.836	0.783	0.787
Global_05_(i)_1	3.43	1.194	0.689	0.847	0.858

Table 4. Reliability Analysis of Full Physical Health Scale

Item Reliability Statistics

				if item dropped	
	mean	sd	item-rest correlation	Cronbach's α	McDonald's ω
Global_01_(i)_1	2.70	1.15	0.704	0.621	0.624
Global_03_(i)_1	2.65	1.20	0.650	0.651	0.658
Global_09r_(i)_1	3.14	1.15	0.471	0.751	0.778
Global_06_(i)_1	1.76	1.06	0.426	0.770	0.801

Table 5. Reliability Analysis of Neuro-QOL Scale

Item Reliability Statistics

				if item dropped	
	mean	sd	item-rest correlation	Cronbach's α	McDonald's ω
pa_wellbe_1	3.28	0.832	0.760	0.919	0.920
pa_wellbe_2	3.09	0.930	0.739	0.919	0.921
pa_wellbe_3	3.13	0.940	0.790	0.916	0.918
pa_wellbe_4	3.50	1.092	0.742	0.919	0.922
pa_wellbe_5	3.55	1.078	0.772	0.917	0.921
pa_wellbe_6	3.08	0.929	0.728	0.920	0.922
pa_wellbe_7	3.96	1.061	0.678	0.923	0.926
pa_wellbe_8	2.97	1.063	0.730	0.920	0.922
pa_wellbe_9	3.13	1.058	0.716	0.921	0.923

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