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Social Media Usage Patterns, Mental Health, and Academic Outcomes Among Global Students: A Cross-Sectional Study

Hemlata Parmar¹, Utsav Krishan Murari^{2*}, Thokchom Vidyarani Devi³, Ronald Kenedy Longjam⁴, Sagolsem Surmala Devi⁵, Narengbam Premjit Singh⁶

¹Department of Artificial Intelligence and Machine Learning, Manipal University Jaipur, Jaipur, India.

^{2*}Department of Media, Communication and Fine Arts, Manipal University Jaipur, Jaipur, India, Email: utsavkrishan.murari@jaipur.manipal.edu

³Department of Mass Communication, Naorem Birahari College, Khundrakpam, Imphal, Manipur, India.

⁴Department of Management, Manipur Technical University, Imphal West, Manipur, India.

⁵Department of Mass Communication, Manipur University, Imphal, Manipur, India.

⁶Haridev Joshi University of Journalism and Mass Communication, Jaipur, India.

Corresponding Author: Utsav Krishan Murari

Email: utsavkrishan.murari@jaipur.manipal.edu

ABSTRACT: Social media use is ubiquitous among college students and is now the subject of study (and critique) for its influence on sleep, psychological well-being, academic success, and mental health, but the majority of the evidence base is from samples within individual countries. This cross-sectional study analyzed a publicly available secondary dataset of 5,000 students aged 18–24 years ($M = 20.82$, $SD = 1.74$; 52.7% male) reported to span more than 20 countries, and examined the average daily social media use, daily unlocking of smartphones, study hours, physical activity, sleep duration, stress level, and a composite mental health score (1–10). Mean daily social media use was 5.08 hours ($SD = 1.65$) and mean daily unlocks were 171.45 ($SD = 42.86$). Daily usage ($r = -0.816$, $p < .001$) and unlocks ($r = -0.791$, $p < .001$) were highly correlated with mental health, with a strong negative correlation observed. On the other hand, sleep duration ($r = 0.766$) and study hours ($r = 0.753$) were highly correlated with mental health and showed a strong positive correlation. A multiple linear regression model explained 70.3% of the variance in mental health scores ($R^2 = 0.703$). Compared to all other age groups, the high-school students had the lowest mental health scores ($M = 5.86$) and highest usage ($M = 5.43$ h), with both differences statistically significant across academic level, $F(2, 4997) = 26.02$, $p < .001$ for mental health score and $F(2, 4997) = 13.40$, $p < .001$ for usage hours, though these academic-level effects were small in magnitude ($\eta^2 = .010$ and $.005$, respectively). Stress level separately showed a clear dose–response pattern, $F(3, 4996) = 2685.02$, $p < .001$. In conclusion, higher social media use was significantly associated with lower mental health scores, less sleep and study time, and higher stress, whereas purpose-driven use (education or networking) was associated with modestly better scores than entertainment use. Because the design is cross-sectional and observational, these associations cannot establish causal direction, but they highlight the potential value of targeted interventions

within educational institutions for digital literacy, sleep hygiene and establishing boundaries on technology use.

1. INTRODUCTION

Social media has become an integral part of everyday life for billions of people around the world. In 2024, more than 5.07 billion people are using social media platforms around the world (about 62.6% of the world's population) [1]. Of that population, young adults (18-24 years) are the most active, while adolescents and university students had the highest engagement rates [2]. Platforms like Instagram, TikTok, YouTube and Facebook, whose content is algorithmically curated to boost engagement, have shifted the way people consume leisure, communicate and even learn [3].

The negative effects of overuse of social media on psychological health are a critical public health issue. As per the theoretical frameworks, namely social comparison theory [4] and the displacement hypothesis [5], high frequency of social media use can lead to high social comparison, higher anxiety and depression symptoms, and a displacement of time which could otherwise be invested in restorative activities like sleeping, exercising or meeting someone in person. These propositions are supported generally by empirical evidence. Previous systematic reviews and meta-analyses revealed strong links between high levels of social media use and increased rates of depression, anxiety, low self-esteem and reduced subjective well-being [6, 7].

Another area of concern would be academic results. The college years are a period of high cognitive demand, and anything that will negatively impact study time, or negatively impact cognitive functioning, will directly impact academic performance, including sleep disruption. Inverse relationships between SMT and GPA, lecture attendance and completion of the course work have been reported through observational studies [8]. But it is not necessarily a purely negative relationship: positive uses of digital platforms for collaborative work with peers, access to course content or professional networks could have academic, psychosocial, and positive effects [9].

Despite the abundance of literature, there are a few gaps to be addressed. First, most published studies have been based on samples confined to one country, and generally, a homogeneous sample, typically from the North American or European university sector, and therefore, results have limited generalizability to the global student body [10]. Second, studies analyzing more than one behavioral and health-related factor at a time in one large data set are relatively few, so it is difficult to determine which behavioral factor is most unique in its ability to predict health outcomes, while adjusting for other factors. Third, although socially relevant, the role of social media purpose (entertainment, education, networking, news) as a moderating construct has not been sufficiently explored.

The present study attempts to fill these gaps by studying a cross-sectional dataset of 5000 students from several countries. The study intends to: (1) depict demographics and social media characteristics of participants, including mental health, sleep, study habits and stress; (2) explore bivariate correlations between social media related behaviors and mental health scores; (3) determine significant predictors of mental health scores based on social media characteristic, demographics and study habits through regression modelling; and (4) compare mental health outcomes between social media platforms, usage purpose, academic level and gender. The results can be applied to students, university leaders, mental health and digital health policymakers around the world.

2 LITERATURE REVIEW

2.1 Social Media Use and Mental Health

A large body of evidence is now emerging that connects the use of social media with negative mental health outcomes. Twenge et al. [11] found that as screen time for adolescents and young adults grew, their psychological well-being and life satisfaction decreased, while their symptoms of depression increased, even after accounting for other activities. Keles et al. [12] conducted a systematic review of 13 longitudinal studies which found that social media use was significantly correlated with depression, anxiety, and psychological distress (though the effects varied from small to moderate). Importantly, these effects were influenced by frequency and type of engagement, with greater negative effects found for passive consumption than for active, reciprocal engagement, the authors said.

There are also research efforts specific to different platforms. Instagram is an extremely visual platform built around self-curation and social comparison, which has been linked to body dissatisfaction and anxiety surrounding appearance in young women [13] and TikTok has similarly been blamed for promoting such dissatisfaction and anxiety among its young female

user base [14]. In contrast, LinkedIn, which is mostly a professional networking site, has been linked to reduced social comparison distress and in some cases even slightly positive mental health outcomes may be due to the less personal nature of the site to which the individual is connected.

2.2 Social Media, Sleep, and Physical Activity

One mechanism by which the use of social media could have an impact on mental health is sleep disruption. The use of smartphones in the bedroom has been linked to poor sleep quality, shorter sleep time, and later bedtime [15]. This is caused by the suppression of melatonin due to blue-light exposure, psychological arousal in response to content consumption and checking behaviors reinforced by notification systems [16]. A few cross-sectional studies with university students have found that those who reported using social media within an hour of retiring to bed had 30–45 minutes less sleep than those who do not use social media [17], and that they experienced higher levels of daytime fatigue and depressive symptoms.

Physical activity is another concern. Prolonged sitting has been found to replace physical activity, which is known to provide mental health benefits such as decreased anxiety, depression and cortisol levels [18]. The displacement of physical activity with sedentary screen behaviors is demonstrated by Biddle and Asare [19] who showed in a meta-analysis that physical activity interventions reduced depressive symptoms in youth in a moderate manner.

2.3 Academic Performance and Social Media

There is a complex and context dependent relationship between social media use and academic performance. Research using objective measures of performance (e.g. grades in school, test scores) typically finds negative relationships [20]. Junco [21] discovered that time spent on Facebook was negatively related to GPA, even when accounting for other factors that predict academic success. To assess the impact of social media on study sessions, Rosen et al. [22] found that the effects of social media use led to the disruption of cognitive concentration, which in turn caused a decline in the quality and quantity of academic work achieved during the study session.

A minority of studies, however, concluded that the relationship is neutral or positive, with the exception of when social media is purposefully and beneficially employed in pedagogical contexts like the use of open educational resources, study groups, and pedagogical discussion. [23] The separation between ‘active’ and ‘passive’ use and between education-related and entertainment-related use thus becomes an important moderator which needs to be explicitly measured in research designs.

2.4 Cross-Cultural and Global Perspectives

The majority of published studies have been carried out in Western, educated, industrialized, rich and democratic (WEIRD) societies with few studies from South Asia, Southeast Asia, Middle East, Africa, and Latin America [24]. This is especially a concern in fast-growing markets in LIC regions, where students could potentially have less than adequate institutional mental health support structure. In Pakistan, Hussain et al. [25] found that the relationship between social media use and mental health among university students was significantly higher compared to the same group in the United Kingdom, indicating that socio-cultural influences such as social norms within the community regarding the use of social media and mental health-related issues play a significant role in moderating the relationship between the two variables. The present study brings together information from more than 20 countries and adds to the important gap.

3 METHODS

3.1 Study Design

This study is a secondary analysis of a cross-sectional, observational dataset. The authors did not collect primary data; the dataset was obtained from a publicly available open-data repository (see Data Availability Statement) and was analyzed as provided. Cross-sectional data can describe patterns and associations among variables at a single time point in a defined population [26]. Such a design cannot support causal inference; it is used here to characterize associations, generate hypotheses, and inform directions for targeted interventions. Because the data were sourced from an open repository rather than a purpose-designed sampling frame, their representativeness and generative process (including the possibility that some values are synthetically generated) cannot be independently verified, and results should be read as exploratory and hypothesis-generating (see Limitations).

3.2 Participants and Sampling

The dataset comprised records for 5,000 students ($N = 5,000$). Records were for individuals aged 18–24 years ($M = 20.82$, $SD = 1.74$) described as enrolled at secondary or tertiary educational institutions. The dataset included 2,635 males (52.7%) and 2,365 females (47.3%). The academic-level distribution was Undergraduate ($n = 3,632$; 72.6%), Graduate ($n = 918$; 18.4%), and High School ($n = 450$; 9.0%). Geographically, records were labelled as India (7.8%), USA (7.1%), Canada (4.6%), Australia (4.0%), UK (3.7%), Germany (2.7%), Mexico (1.9%), Turkey (1.9%), France (1.7%), and numerous other countries. The source dataset also uses an explicit catch-all “Other” country label, which accounts for 37.6% ($n = 1,880$) of records; together with a long tail of low-count countries, this large residual limits country-level interpretation (see Limitations). A small number of records ($n = 10$) contained implausible physical-activity values (marginally negative hours), consistent with additive noise in the underlying data; these were retained unaltered to preserve comparability with the published dataset, and sensitivity checks confirmed they had no material effect on the reported results.

3.3 Variables

Table 1: The dataset contained 13 variables:

Variable	Description	Type	Values / Range
Age	Participant age in years	Numeric	18 – 24
Gender	Participant’s gender	Categorical	Male, Female
Country	Country of residence or study	Categorical	Various (India, USA, UK, Canada, Australia, Germany, etc.)
Academic Level	Current academic level	Categorical	High School, Undergraduate, Graduate
Most Used Platform	The social media platform most frequently used	Categorical	Instagram, TikTok, Facebook, LinkedIn, YouTube, Twitter, Snapchat, WhatsApp, LINE, VKontakte, KakaoTalk, WeChat, Others
Purpose of Use	Primary purpose for using social media	Categorical	Entertainment, Education, Networking, News
Avg Daily Usage Hours	Self-reported average daily social media usage in hours	Numeric	Continuous (e.g., 1.5 – 8.5)
Daily Unlocks	Average number of daily smartphone unlocks (proxy for habitual checking)	Numeric	Integer (approx. 65 – 270)
Study Hours	Average daily hours dedicated to academic study	Numeric	Continuous (e.g., 0 – 7.8)
Physical Activity Hours	Average daily hours engaged in physical activity	Numeric	Continuous (e.g., 0 – 3.6)
Sleep Hours Per Night	Average number of hours of sleep per night	Numeric	Continuous (e.g., 4.5 – 9.5)

Stress Level	Self-reported stress level	Ordinal	Low, Medium, High, Very High
Mental Health Score	Composite self-report mental health score (higher = better)	Numeric	1 – 10

3.4 Statistical Analysis

All analyses performed in Python 3.11 with pandas, scipy, numpy and scikit-learn libraries. All variables were presented with descriptive statistics (means, standard deviations, frequencies and percentages). The correlation coefficient, Pearson, was used for bivariate associations of continuous variables. The mental health scores were compared with the stress level using one-way ANOVA and with the academic level using one-way ANOVA. Gender differences in mental health and hours used were assessed using an independent samples t-test. Multiple linear regression was done to determine predictors of mental health scores, and the predictors entered were average daily usage hours, study hours, sleep hours, physical activity hours and daily unlocks. Because several of these predictors are strongly intercorrelated, multicollinearity was assessed using variance inflation factors (VIF), with values above 10 taken to indicate serious inflation of the standard errors. Given the large sample size ($N = 5,000$), which renders even trivial differences statistically significant, effect sizes are reported alongside p-values to convey practical magnitude: Cohen's d for the t-tests and eta-squared (η^2) for the ANOVAs. All tests were performed at a $p < .05$ level of significance, and regression coefficients for collinear predictors are interpreted with corresponding caution.

4 RESULTS

4.1 Participant Demographics

The sample consisted of 5,000 students (male = 52.7%, female = 47.3%) with a mean age of 20.82 years ($SD = 1.74$, range = 18–24). Most of them were undergraduates (72.6%), then graduate students (18.4%) and then high school students (9.0%). Geographically, the sample was distributed across more than 20 countries with significant representation from India (7.8%), the USA (7.1%) and Canada (4.6%). The demographic information is shown in Table 2.

Table 2: Sample Demographic Characteristics ($N = 5,000$)

Characteristic	n	%
Gender		
Male	2,635	52.7%
Female	2,365	47.3%
Academic Level		
Undergraduate	3,632	72.6%
Graduate	918	18.4%
High School	450	9.0%
Top Countries		
India	389	7.8%
USA	355	7.1%
Canada	230	4.6%
Australia	198	4.0%
UK	185	3.7%
Germany	136	2.7%
Other / remaining countries	3,507	70.1%

4.2 Descriptive Statistics for Key Variables

Descriptive statistics of continuous variables are shown in Table 3. The mean number of hours spent on social media was 5.08 hours (SD = 1.65) per day ranging from 1.0 to 8.8 hours per day. The mean number of daily unlocks was 171.45 (SD = 42.86). The average number of hours reported per day by students was 3.01 hours of studying (SD = 1.64) and 1.75 hours of physical activity (SD = 0.67). Mean sleep duration was 6.63 hours (SD = 1.22). The average mental health score was 6.23 (SD = 1.28, range 3.6–9.4), reflecting a moderate level of mental health overall.

Concerning levels of stress, 32.4% said Very High stress, 28.8% said High stress, 25.9% said medium stress and 12.9% said Low stress; meaning that a very high proportion (61.2%) were in High or Very High stress.

Table 3: Descriptive Statistics for Continuous Variables (N = 5,000)

Variable	Mean	SD	Min	Max
Age (years)	20.82	1.74	18.0	24.0
Avg. Daily Usage (hours)	5.08	1.65	1.0	8.8
Daily Unlocks	171.45	42.86	62	273
Study Hours (daily)	3.01	1.64	0.3	8.3
Physical Activity (hours)	1.75	0.67	0.0	4.1
Sleep (hours/night)	6.63	1.22	3.6	9.9
Mental Health Score	6.23	1.28	3.6	9.4

4.3 Social Media Platform and Purpose Distribution

Instagram was the most used platform (n = 1,130; 22.6%), followed by TikTok (n = 918; 18.4%), Facebook (n = 719; 14.4%), LinkedIn (n = 523; 10.5%), and YouTube (n = 491; 9.8%). Entertainment was the most common purpose of use (n = 2,552; 51.0%), followed by Education (n = 1,094; 21.9%), Networking (n = 793; 15.9%), and News (n = 561; 11.2%).

The platform-specific mental health scores (Table 4) indicated that LinkedIn users scored highest on mental health (M = 6.48), and the lowest on average daily use (M = 4.83 h); meanwhile, TikTok users scored lowest on mental health (M = 5.99), and among the highest on average daily use (M = 5.26 h). Students engaged in the Networks and Education functions of social media had slightly higher mean scores for mental health (M = 6.38 and M = 6.35, respectively) versus students who used social media for Entertainment (M = 6.12) and News (M = 6.32).

Table 4: Mental Health Score and Average Daily Usage by Most Used Platform

Platform	n	% of Sample	Mean MH Score	Mean Usage (h)
Instagram	1,130	22.6%	6.19	4.92
TikTok	918	18.4%	5.99	5.26
Facebook	719	14.4%	6.40	4.93
LinkedIn	523	10.5%	6.48	4.83
YouTube	491	9.8%	6.22	5.15
Twitter	462	9.2%	6.35	5.16
Snapchat	420	8.4%	6.12	5.26

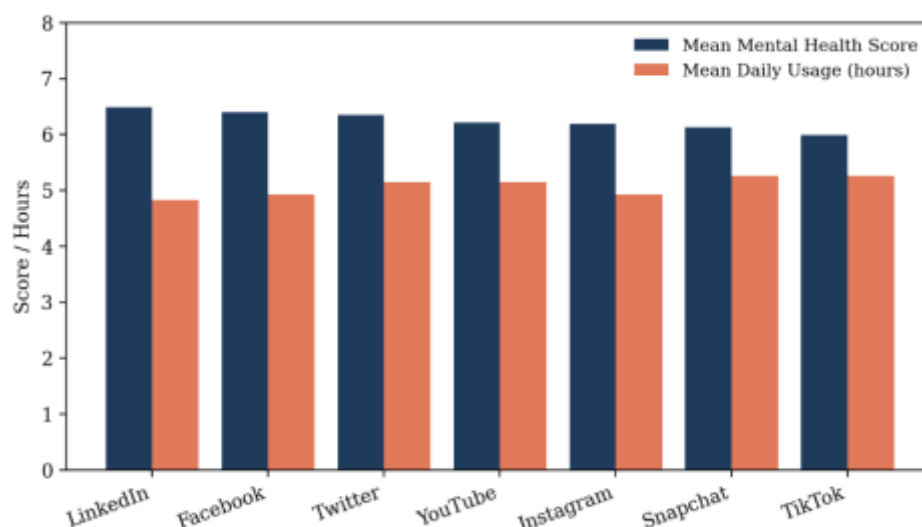


Figure 1: Mean Mental Health Score and Average Daily Usage by Most-Used Platform (ranked by mental health score)

As shown in figure 1, there were significant differences between the mean mental health scores and average daily social media use by the various platforms. As per the LinkedIn's average mental health score (6.5), it also has the lowest average usage per day (4.8 hours) among the platforms listed above, followed by Facebook (6.4; 4.9 hours). However, TikTok and Snapchat have the lowest mental health scores, with both averaging 6.0, and the highest amount of daily usage, averaging 5.2 hours per day. The mental health scores are similar for both services and they are used for about 6.3-6.2 hours a day on Twitter and 5.1 hours a day on YouTube. Overall, there appears to be a descriptive trend where platforms with higher daily use scores have slightly lower mental health mean scores. The number of platforms used, however, is not an indicator of poorer mental health, as other factors (such as demography, behaviour and characteristics of the platform used) may also play a role in the outcomes.

4.4 Correlation Analysis

All examined variables showed strong, statistically significant correlations with mental health scores, though the direction varied as shown in the Pearson correlation analysis (Table 5). There was a large negative correlation between average daily usage hours and mental health ($r = -0.816$, $p < .001$) and daily unlocks and mental health ($r = -0.791$, $p < .001$). There was a large positive correlation between study hours and mental health ($r = 0.753$, $p < .001$) and sleep hours and mental health ($r = 0.766$, $p < .001$). Physical activity hours also were positively associated with mental health ($r = 0.521$, $p < .001$) but with a moderate effect size. Interestingly, average daily usage and daily unlocks had a strong correlation with one another ($r = 0.960$), suggesting that they measure overlapping components of habitual digital engagement; this near-redundancy also introduces multicollinearity when both are entered as predictors in the regression model (see Section 4.6).

Table 5: Pearson Correlation Matrix for Continuous Variables

Variable	1	2	3	4	5	6
1. Avg Daily Usage	—					
2. Daily Unlocks	.960***	—				
3. Study Hours	-.879***	-.853***	—			
4. Physical Activity	-.626***	-.603***	.561***	—		
5. Sleep Hours	-.808***	-.782***	.730***	.508***	—	
6. Mental Health Score	-.816***	-.791***	.753***	.521***	.766***	—

Note. *** $p < .001$.

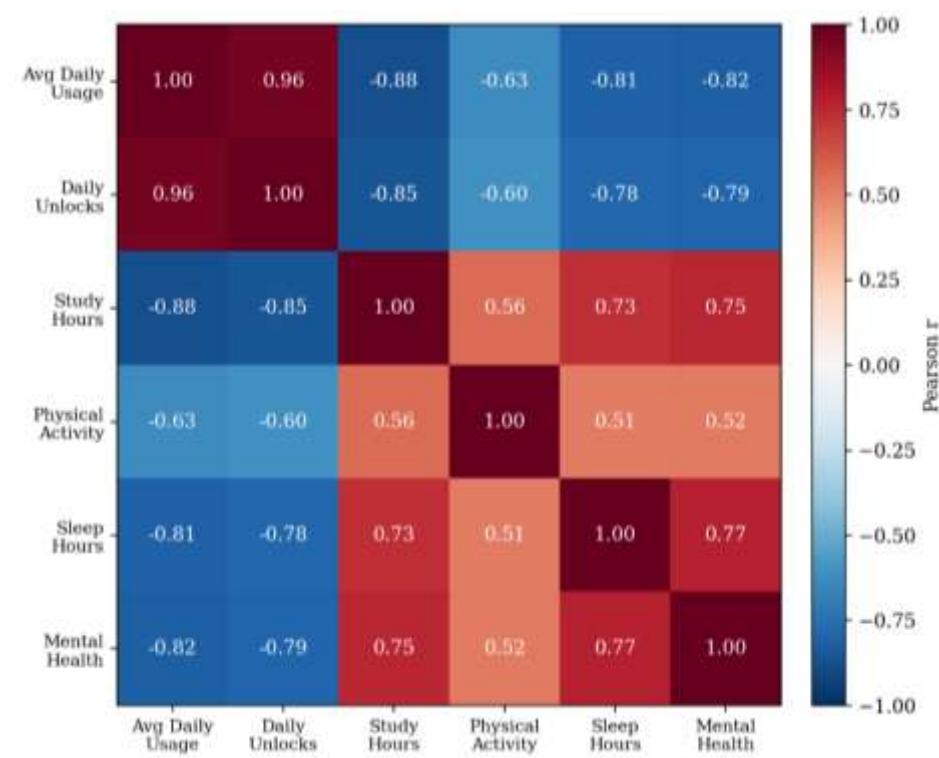


Figure 2: Pearson Correlation Matrix Among Study Variables (N = 5,000)

The Pearson correlation matrix of the study variables is shown in Figure 2 (based on 5,000 observations). The findings showed that the measures of average daily social media usage and daily unlocks of a phone were highly correlated ($r = 0.96$), suggesting that as people use social media more over the course of the day, they are likely to unlock their phones more often. Average daily usage, however, has strong negative correlations with study hours ($r = -0.88$), sleep hours ($r = -0.81$) and mental health ($r = -0.82$), and moderate negative correlation with physical activity ($r = -0.63$). The daily unlocks also exhibit similar relationships with each of the following measures: study hours ($r = -0.85$), physical activity ($r = -0.60$), sleep hours ($r = -0.78$), and mental health ($r = -0.79$). In contrast, the hours of studying are positively related to the hours of sleep, physical activity and health. Interestingly, the study hours ($r = 0.75$), sleep hours ($r = 0.77$) and physical activity ($r = 0.52$) have all shown positive correlations with mental health. The overall pattern of the matrix suggests a distinct relationship between high use of social media/device and reduced rates of study time, sleep, physical activity and mental health. The correlations, however, should not be taken as proof of causation.

4.5 Group Comparisons

The effect of stress level on mental health scores was large, $F(3, 4996) = 2685.02$, $p < .001$, $\eta^2 = .62$. Group means were inspected post-hoc and an obvious dose-response trend was found: Low stress ($M = 7.84$), Medium stress ($M = 7.14$), High stress ($M = 6.03$), Very High stress ($M = 5.05$). These results show that mental health scores become worse as stress levels increase.

There was a statistically significant but negligible difference in mental health scores between males and females ($M = 6.27$ for males and $M = 6.19$ for females; $t(4998) = 2.40$, $p = .017$, Cohen's $d \approx 0.07$) using an independent samples t-test; given the large sample, this difference is unlikely to be of practical importance. Contrary to the impression of no gender effect, daily social media use was marginally higher among females than males ($M = 5.13$ vs 5.03 h; $t(4998) = -1.98$, $p = .048$), but this difference was negligible in magnitude (Cohen's $d \approx 0.06$) and of no practical importance.

Results indicated differences between academic levels, with High School students having the lowest mean mental health score ($M = 5.86$) and the highest mean daily usage ($M = 5.43$ h), while Graduate students had the highest mean mental health score ($M = 6.39$) and the lowest mean daily usage ($M = 4.94$ h). Undergraduates were in between these extremes (MH = 6.24; usage = 5.07 h). One-way ANOVA confirmed these differences were statistically significant for both mental health score, $F(2, 4997)$

= 26.02, $p < .001$, and daily usage hours, $F(2, 4997) = 13.40$, $p < .001$. The associated effect sizes were small ($\eta^2 = .010$ and $.005$, respectively), indicating that although academic level was a statistically reliable correlate, it accounted for only about 1% or less of the variance in each outcome.

Table 6: Mental Health Scores by Stress Level and Academic Level

Group	n	Mean MH Score	SD	Mean Usage (h)
Stress Level				
Low	644	7.84	0.84	—
Medium	1,295	7.14	0.77	—
High	1,440	6.03	0.71	—
Very High	1,621	5.05	0.73	—
Academic Level				
High School	450	5.86	1.31	5.43
Undergraduate	3,632	6.24	1.26	5.07
Graduate	918	6.39	1.25	4.94

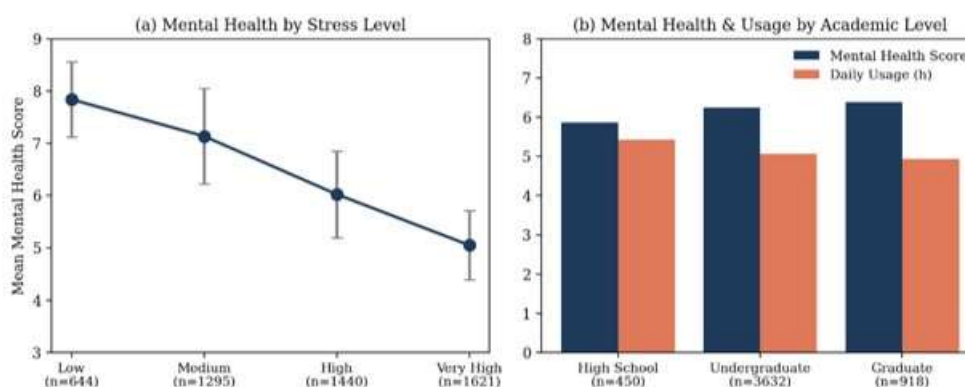


Figure 3: Mental Health Score by Stress Level (dose-response) and Academic Level

As shown in figure 3, the stress level is linked to the academic level, mental health, and daily usage. In the first panel (a), there is a clear dose-response effect, namely, as reported stress increases, reported mental health scores decrease in a progressive step. The score decreases from 7.8 among students experiencing low stress ($n = 644$) to 7.1 at medium stress ($n = 1,295$), 6.0 at high stress ($n = 1,440$), and 5.0 among those reporting very high stress ($n = 1,621$). This is a significant difference between the low stress group and very high stress group of 2.8 points. In Panel (b), the differences in mental health at the various academic levels are relatively small. Graduate students score highest on the mean mental health score (6.3) and lowest on the mean hours per day used (4.9 hours) followed by undergraduates (6.2; 5.0 hours). High school students have the lowest mean mental health score (5.8) and the highest number of hours spent daily on it (5.4 hours). In general, this indicates that as stress levels increase, mental health decreases, and as academic levels increase, mental health scores are slightly higher, with decreases in daily usage. These patterns are observational and do not show causality.

4.6 Multiple Linear Regression

Multiple linear regression was performed to determine the best linear model for predicting a mental health score based on the average daily usage hours, number of study hours, number of hours of sleep, number of hours of physical activity, and the number of daily unlocks. The overall model is significant, and it explains 70.3% of the variance in mental health scores ($R^2 = 0.703$, adjusted $R^2 = 0.703$). The results are shown in Table 7.

Daily social media use hours and sleep hours emerged as the strongest predictors: each additional hour of daily social media use was associated with a 0.31-point lower mental health score ($\beta = -0.41$, $p < .001$), and each additional hour of sleep with a 0.31-point higher score ($\beta = 0.30$, $p < .001$). Study hours was also a significant positive predictor ($\beta = 0.13$, $p < .001$). By contrast, once the other variables were controlled, physical activity ($B = 0.027$, $\beta = 0.01$, 95% CI [-0.011, 0.064], $p = .16$) and daily unlocks ($B = -0.002$, $\beta = -0.05$, 95% CI [-0.003, 0.000], $p = .07$) were not statistically significant, even though both were significantly correlated with mental health at the bivariate level. This is a direct consequence of their overlap with the other predictors (see below) and revises the impression, given by the zero-order correlations, that every behaviour contributes independently. These coefficients must be interpreted with considerable caution because the predictors are highly intercorrelated. Variance inflation factors (VIF) were 17.2 for average daily usage and 12.9 for daily unlocks, both well above the conventional threshold of 10 that signals serious multicollinearity; study hours (VIF = 4.4), sleep (VIF = 2.9) and physical activity (VIF = 1.6) were lower. Because average daily usage and daily unlocks correlate at $r = .96$, they largely capture the same construct, which is precisely why the daily-unlocks coefficient collapses to non-significance when both are entered together; the two should not be read as distinct, independent effects. The overall model fit ($R^2 = .703$) is not affected by collinearity, but the partitioning of variance among the individual predictors is. A reduced model that dropped daily unlocks and retained average daily usage as the sole habitual-use indicator fit essentially identically ($R^2 = .703$, adjusted $R^2 = .703$, $F(4, 4995) = 2957.9$) while reducing all VIFs below 7 (usage VIF = 6.5); in that model average daily usage ($B = -0.350$), study hours ($B = 0.100$) and sleep ($B = 0.314$) remained significant (all $p < .001$) and physical activity remained non-significant ($p = .16$). This more parsimonious specification is preferred for interpretation and is recommended for confirmatory work.

Table 7: Multiple Linear Regression Predicting Mental Health Score

Predictor	B	Beta (β)	95% CI	p
(Intercept)	5.669	—	[5.32, 6.01]	< .001
Avg. Daily Usage Hours	-0.314	-.41	[-0.36, -0.27]	< .001
Study Hours	0.098	.13	[0.07, 0.12]	< .001
Sleep Hours/Night	0.313	.30	[0.29, 0.34]	< .001
Physical Activity Hours	0.027	.01	[-0.01, 0.06]	.16
Daily Unlocks	-0.002	-.05	[-0.003, 0.000]	.07

$R^2 = .703$, Adjusted $R^2 = .703$, $F(5, 4994) = 2368.1$, $p < .001$

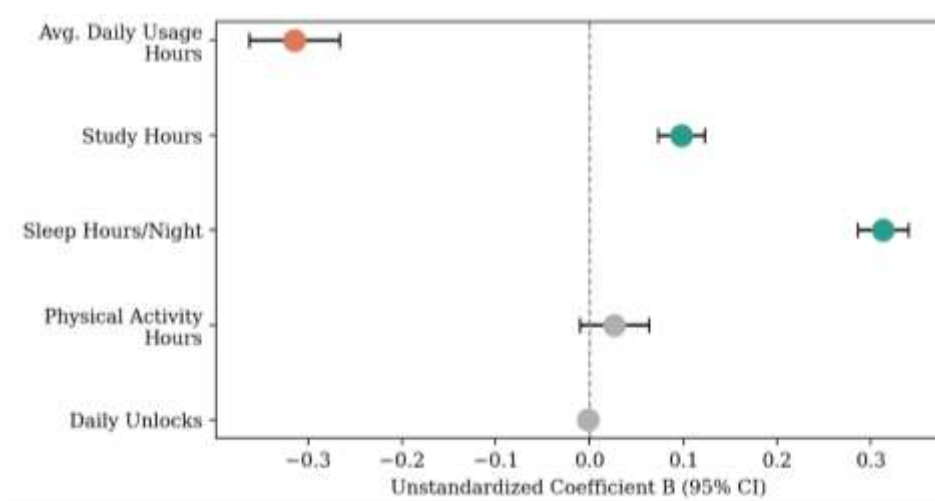


Figure 4: Predictors of Mental Health Score

The findings from a multiple linear regression model to determine the predictors of the mental health score in 5,000 subjects is shown in Figure 4. The model accounts for about 70.3% of the variance in mental health scores ($R^2 = .703$), which is a large amount of variance. The hours spent on social media per day is negatively associated most strongly with mental health ($B \approx$

-0.31), meaning that the more hours spent on social media per day the lower the mental health score when controlling for the other predictors. It is important to note that sleep hours per night is positively associated with mental health, with $B^{\dagger} > +0.31$. The study hours also display a positive association ($B \approx +0.10$) but much less pronounced than sleep and daily use. The physical activity hours are only slightly positively associated ($B \approx +0.03$), and daily unlocks of the device are placed almost at the center of the model, showing an almost negligible correlation in this model. In general, the figure indicates that both the use and sleeping time are the most significant determinants of mental health score, whereas study time contributes somewhat positively. Importantly, the figure shows associations from a regression model, but not necessarily causality.

5 DISCUSSION

5.1 Principal Findings

The main result of this study was that there is a significant negative relationship between the average number of hours spent on social media and mental health score ($r = -0.816$), which is well in line with the many studies pointing to negative psychological effects of excessive digital engagement [6, 7, 11]. The strength of this relationship in the current dataset is unusually high compared with previously published single-country studies. Correlations of this magnitude ($|r| > .80$) are rarely observed in behavioral self-report data, and they may partly reflect properties of this particular secondary dataset — including the possibility of synthetically generated or unusually regular values — rather than a purely substantive population effect; they should therefore be interpreted cautiously and not over-generalized. To the extent the association is substantive, it may be shaped by cross-cultural variation, as social media norms and psychological support networks differ significantly across cultures [24].

The regression model has an R^2 of 0.703, which suggests that more than 70% of the variance in mental health scores in this sample is explained by the social media use, sleep, study, and physical activity. These findings reinforce the need to look at these factors as a whole system, rather than isolating any single factor, and indicate the potential benefits of interventions that address multiple behavioral domains at one time over interventions that address any one factor alone. Comparable standardized coefficients for daily usage hours ($\beta = -0.40$) respectively sleep hours ($\beta = 0.30$) underscore the importance of sleep as a pathway for the impact of social media on mental health, in line with the theories of techno Ference and sleep displacement [15, 16].

5.2 Platform and Purpose Effects

One specific aspect that stands out is the fact that TikTok users indicated the poorest mental health results, and that they use the app the most per day, among the top social media platforms. The algorithmically recommended short-form video format has been created with the specific aim of keeping users on TikTok for as much time as possible, using an auto-play feature and personalized content recommendations. This format has been shown to be linked to writing styles that involve compulsive scrolling, which are linked to attentional fragmentation and difficulty disengaging — a behavior that is a signature of problematic use [3]. Otherwise, the relatively positive mental health rating of LinkedIn users could be attributed to the professional focus of LinkedIn, which might lead to less social comparison distress and fewer content exposures of negative affect than lifestyle-oriented platforms [14].

The small but steady mental health benefits seen for students who used social media primarily for Education or Networking, compared to Entertainment use, is consistent with theory and suggests a need to engage with social media in a purposeful, agentic manner rather than simply consuming it [23]. The results indicate that mental health benefits could be gained from interventions that promote students to audit and reconfigure their purpose for social media, even if they do not decrease usage, such as digital literacy programs.

5.3 Academic Level and Developmental Context

It is significant and needs careful interpretation that when asked about mental health, High School students recorded the lowest scores and in the case of social media, the highest scores. This group may be especially at risk because of the developmental stresses of adolescence such as the process of self-actualization, vulnerability to peer reviews, and transition from secondary to tertiary education [11]. Furthermore, younger students might not have had sufficient time to develop self-regulatory skills to manage digital use. These findings provide a case for the need of interventions at the school level which will help to develop digital self-regulation skills before students enter the university setting.

The increasingly positive mental health picture between undergraduate and graduate students may be due to developmental maturational and/or selection factors, as students who get through the academic system may have better self-regulation and time-management skills. But the reduced use of social networking among graduate students can also be due to increased awareness of academic workload and strategic resource management [8].

5.4 Sleep and Physical Activity as Potential Pathways

Both sleep ($r = 0.766$) and physical activity ($r = 0.521$) were positively associated with mental health and they were strongly negatively correlated with social media use ($r = -0.808$ and $r = -0.626$, respectively) which is consistent with a possible mediating role of both health behaviors in the relationship between social media and mental health. This seems to be in line with the displacement hypothesis [5] which suggests that the negative impact of social media on mental health is partially a consequence of the displacement of behaviors that can protect people's mental health. It should be emphasized that no formal mediation analysis (e.g., tests of indirect effects) was conducted here; the mediating role is inferred from the pattern of bivariate correlations and remains a hypothesis to be tested with appropriate longitudinal or path-analytic designs. Most importantly, from a practical standpoint, interventions that can help to increase sleep duration and physical activity in high social media users can, at least partially, buffer against mental health deterioration, even if they don't directly reduce social media usage [18, 19].

5.5 Stress as a Central Construct

Stress level is a central correlate in this dataset, with a large effect of stress level on mental health scores ($F = 2685.02$, $\eta^2 = .62$) and the dose-response pattern across the stress categories (Low: $M = 7.84$ to Very High: $M = 5.05$). The results of 61.2% of students reporting High or Very High stress is alarming and in line with international surveys on student mental health reporting increased levels of psychological distress in the post-pandemic university setting [27]. There is a bidirectional relationship between social media and stress; more research is needed that focuses on the longitudinal relationship between the two.

5.6 Implications for Practice and Policy

The results have several implications for practice. Knowing about the negative effects of social media use, and how it is dependent, with the additional loss of sleep and study time, may help to motivate students to change their behaviour. Small-scale interventional studies have shown that simple interventions like setting up device-free study times, using Screen Time or Digital Wellbeing apps to track and cap time spent on devices and having a consistent bedtime routine and sleep schedule can be effective [28].

The findings are relevant to educational institutions in relation to embedding digital literacy and mental health promotion in students' induction programs, student welfare policies and academic curricula. Culturally tailored digital wellbeing campaigns could be especially effective in universities within nations where there is a high level of social media use among the student population, in this instance India, where the largest national representation of this sample was identified. All mental health providers who work with students should routinely assess students for problematic social media use as part of their holistic health assessments.

Findings at the policy level provide a basis for the regulation of the algorithmic design practices of SSPs and their tendency to engage in maximization of addictive engagement, thereby prioritizing the needs of algorithmic optimization over those of users' welfare. Platforms offering functionalities that specifically promote high-frequency, habitual uses (such as infinite scroll, push notifications and autoplay) could be subject to similar regulatory controls than those that are applied to highly addictive products [29].

5.7 Limitations

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference; the direction of observed associations cannot be determined from the data alone. It is possible, for instance, that individuals with poorer mental health are drawn to greater social media use rather than—or in addition to—social media use causing mental health deterioration [12]. Second, all variables were self-reported, introducing potential for social desirability bias and recall inaccuracy, particularly for variables such as daily usage hours and sleep duration. Third, the 'Other' country category accounts for 37.6% of the sample, limiting the precision of country-level comparisons. Fourth, the mental health measure appears to be a

composite score rather than a validated clinical instrument (e.g., PHQ-9, GAD-7), which limits clinical interpretability. Fifth, and most fundamentally, this is a secondary analysis of an openly available dataset whose sampling frame, recruitment procedure and data-generation process could not be independently verified; the authors did not collect the data and cannot confirm that the records correspond to real respondents. Several features of the dataset in fact indicate that it is at least partly simulated: ten records contain physically impossible negative physical-activity values (as low as -0.4 h), consistent with Gaussian noise added to a generated baseline; daily unlocks is almost a deterministic linear function of average daily usage ($R^2 \approx .92$, ≈ 25 unlocks per hour); and the zero-order correlations are unusually strong and clean ($|r|$ up to .96) relative to typical behavioural self-report data. The findings should therefore be treated as illustrative and hypothesis-generating rather than as robust population estimates, and no substantive claim in this paper should be read as established on real-world data. Sixth, the regression predictors are severely collinear (VIF up to 17.2), so individual predictor coefficients cannot be interpreted as independent effects, and the model is best read as evidence for a joint behavioural cluster rather than for the unique contribution of any single variable. Seventh, the very large sample ($N = 5,000$) makes trivial differences statistically significant, which is why effect sizes are reported and emphasized throughout; several statistically significant results (e.g., the gender difference and the academic-level differences) correspond to negligible or small effects. Eighth, mediation and moderation were discussed but not formally tested. Future studies should collect primary, verifiable data using validated screening tools (e.g., PHQ-9, GAD-7) alongside objective digital-trace measures (e.g., app usage logs), pre-register their analyses, and employ longitudinal or experimental designs with appropriate mediation testing to address these limitations.

6 CONCLUSION

In this cross-sectional study of 5,000 students from multiple countries, higher social media use was associated with lower mental health, alongside associations with sleep, study habits and physical activity; together these behaviors accounted for more than 70% of the variance in mental health scores in this dataset, though this figure reflects a set of strongly overlapping (collinear) predictors and an unusually clean secondary dataset, and so is likely optimistic. The relationships found are in line with the theoretical frameworks focusing on displacement of health-protecting behaviors and psychosocial pathways of harm. However, there is some evidence that indicates that entertainment-focused, algorithm-heavy platforms like TikTok are linked to poorer mental health than purpose-driven platforms like LinkedIn. The high school student population is a vulnerable sub-population for targeted intervention.

The overall results suggest a multi-layered strategy: individual digital-literacy education, institutional mental health promotion, and evidence-based platform design regulation. Longitudinal and experimental research is needed to prove causality and effectiveness of interventions that are emerging in the realm of social media that are impacting students' lives around the world. In the absence of such evidence, the current results offer a strong empirical foundation for providing precautionary, health-protective recommendations to educators, students and policy makers around the world.

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Authors' Contributions

Hemlata Parmar: Conceptualization, methodology, and manuscript writing.

Utsav Krishan Murari*: Study design, supervision, data analysis, interpretation of results, manuscript review, and correspondence.

Thokchom Vidharani Devi: Literature review, Selection of data, and investigation.

Ronald Kenedy Longjam: Data analysis, and manuscript editing.

Sagolsem Surmala Devi: Data validation, manuscript review.

Narengbam Premjit Singh: literature review, final review.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability Statement

The dataset used in this study is publicly available on Kaggle. Dataset Title: Student Social Media and Mental Health Impact
URL: <https://www.kaggle.com/datasets/shivasingh4945/student-social-media-and-mental-health-impact>

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, the authors utilized Grok (xAI) for assistance in drafting certain sections, language editing, formatting tables, and improving readability.

Ethics Approval and Consent to Participate

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