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Analysis of Dominant Factors Affecting the Mental Health of Social Media Users

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ABSTRACT

Sleep quality matters most for mental health among social media users—more than screen time, stress, or any demographic factor. We analyzed data from 477 social media users to identify which behavioral and psychosocial factors best predict mental well-being, as measured by a happiness index. Three factors showed significant associations: daily screen time, sleep quality, and stress levels. Respondents who spent more time on screens, slept poorly, and experienced high stress reported worse mental health. But sleep quality dominated. People with good sleep were 5.6 times more likely to report healthy mental wellbeing than those sleeping poorly (OR = 5.559; 95% CI: 2.841-10.878; $p < 0.001$), even after accounting for screen time and stress. Surprisingly, age, gender, physical activity, and platform choice showed no relationship with mental health. These findings challenge the assumption that simply reducing social media use improves wellbeing. Instead, public health interventions should prioritize sleep hygiene alongside, not instead of, managing screen time and stress. In our increasingly digital world, how we rest may matter more than how much we scroll.

Keywords: mental health, screen use, sleep quality, stress, social media.

INTRODUCTION

Social media has woven itself into the fabric of daily life. We wake up to notifications, communicate through direct messages, and scroll through feeds during lunch breaks. What began as a tool for connection now shapes how we access information, maintain relationships, and even understand ourselves. (Rehman et al., 2022). This ubiquity has sparked legitimate concern. If we spend hours each day immersed in digital spaces, what happens to our mental health? The question matters because the stakes are high—rates of anxiety and depression have climbed alongside smartphone adoption, particularly among young adults. Yet despite growing alarm, we lack clarity about which specific factors most strongly predict mental wellbeing among social media users (Shen & Wall, 2021).

Existing research points to several culprits. Screen time appears harmful, disrupting sleep cycles and displacing face-to-face interaction (Kirkbride et al., 2024)(Nakshine et al., 2022). Poor sleep quality erodes emotional regulation. Chronic stress overwhelms coping mechanisms. Physical inactivity compounds the problem. Even demographic characteristics—age, gender—seem to shape vulnerability to mental health problems (Mezzina et al., 2022). But here's what we don't know: how these factors compare when examined together. Previous studies typically isolate single variables, leaving us unable to determine which interventions would actually work best (Mezzina et al., 2022).. Does reducing screen time matter more than improving sleep? Should stress management take priority? Without simultaneous analysis of multiple factors, public health guidance remains fragmented and potentially misdirected (Kirkbride et al., 2024).

This study addresses that gap. We analyzed behavioral, psychosocial, and demographic data from 477 social media users to identify which factors most strongly associate with mental health outcomes. By examining these variables together rather than in isolation, we can determine their relative importance and guide more effective interventions. The analysis uses publicly available data, allowing for objective assessment while generating findings relevant to real-world policy development (Pilar et al., 2022)Our goal is straightforward: provide empirical evidence about what actually matters for mental wellbeing in the digital age, so that prevention efforts can focus on the factors most likely to make a difference.

LITERATURE REVIEW

The evidence linking social media use to mental health tells a complicated story. Screen time clearly correlates with psychological distress, though researchers disagree about how strong that relationship is (Hassan et al., 2022). Some studies find modest effects; others report alarming associations between heavy social media use and depression. Sleep quality emerges consistently as a mediating factor—blue light exposure disrupts circadian rhythms, late-night scrolling cuts into rest time, and poor sleep undermines emotional regulation. Stress levels compound these effects, particularly when social media becomes a source of social comparison or information overload. Physical activity offers potential protection, yet its role in the digital context remains underexplored. Demographic variables further muddy the picture: adolescents appear more vulnerable than adults, though gender effects vary across studies.

What explains these inconsistencies? Methodological choices matter enormously. Studies measuring "screen time" differ in whether they count passive scrolling or active engagement,

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total hours or specific platforms, and self-reported estimates or tracked data. Mental health assessments range from clinical diagnoses to simple mood surveys. Sample populations vary from college students to general adults to specific at-risk groups. These differences make direct comparisons difficult and limit our ability to draw firm conclusions about which factors matter most.

More problematically, most research examines factors in isolation. A study might investigate screen time and depression while controlling for age and gender. Another explores sleep quality and anxiety. A third looks at physical activity and wellbeing. This siloed approach creates a fragmented knowledge base. We know that multiple factors relate to mental health, but we cannot determine their relative importance. Does improving sleep quality offset the harms of high screen time? Would stress management interventions prove more effective than encouraging social media breaks? Without simultaneous analysis, we're essentially guessing about intervention priorities.

This gap has real consequences for public health practice. Interventions targeting single factors—"reduce your screen time," "exercise more," "practice mindfulness"—may miss the mark if they don't address the most influential determinants. Recent calls for evidence-based mental health policy emphasize the need for quantitative analyses that can identify dominant factors and guide resource allocation (Pilar et al., 2022). Our literature review confirms what practitioners suspect: we need comprehensive studies examining behavioral, psychosocial, and demographic factors simultaneously. Only then can we move beyond cataloging correlations toward an actionable understanding of what most powerfully shapes mental health in the digital age.

METHODS

Data Source and Sample

We analyzed the Mental Health and Social Media Balance Dataset, publicly available on Kaggle (Prince7489, 2023). The original data were collected in 2023 through an online survey of active social media users. Using secondary data allowed us to conduct objective analysis efficiently while examining a comprehensive set of variables relevant to our research questions. The dataset is accessible at: https://www.kaggle.com/datasets/prince7489/mental-health-and-social-media-balance-dataset.

The initial dataset contained 500 respondents. We cleaned the data by removing observations with incomplete information on key variables and categories with minimal frequencies. The gender variable included an "other" category with too few observations for reliable statistical analysis, so we excluded these cases from multivariate modeling. Our final analytical sample comprised 477 social media users.

Variables and Measurement

Mental health served as our dependent variable. We used the Happiness Index—a 1-10 scale in which higher scores indicate better mental well-being—as a proxy measure. While imperfect, happiness indices capture subjective well-being in ways that meaningfully correlate with more comprehensive mental health assessments.

Independent variables fell into two categories. Demographic factors included age and gender. Behavioral and psychosocial factors included daily screen time, sleep quality, stress level, frequency of physical activity, and days without social media use. These variables capture the multidimensional nature of digital life and its potential mental health impacts.

Statistical Analysis

We analyzed three stages. First, descriptive statistics characterized our sample and the distributions of the variables. Second, bivariate Chi-Square tests examined relationships between each independent variable and mental health status. This step identified which factors warranted inclusion in multivariate modeling. Third, we employed logistic regression to assess the simultaneous effects of significant predictors on mental health. This approach reveals which factors remain important after accounting for others—essential for understanding relative influence.

We report regression coefficients, p-values, odds ratios (OR), and 95% confidence intervals. All analyses were conducted using IBM SPSS Statistics version 27. Because we analyzed cross-sectional observational data, our findings reflect statistical associations rather than causal relationships. We cannot determine whether poor sleep causes mental health problems, for example, or whether mental health problems disrupt sleep. Both likely occur.

Ethical Considerations

The dataset operates under a public domain license and contains no personally identifiable information. Because the data were already anonymized and publicly accessible, our institutional guidelines did not require formal ethical approval for this secondary analysis. We nonetheless adhered to ethical data-use principles: properly citing sources, using data solely for research purposes as permitted by the platform's terms, and transparently reporting our methods and limitations.

RESULTS

Based on Table 1, the majority of respondents were male (52%) and in the adult age group (31%), followed by late adults (29%) and young adults (26%). The majority of respondents had moderate daily screen time (51%) and adequate sleep quality (66%). In terms of stress levels, the majority of respondents were in the high category (54%), while based on social media usage frequency, most respondents were in the occasional category (51%). In terms of physical activity, the majority of respondents reported low levels (44%), followed by moderate (39%). By social media type, the most widely used platform was TikTok (19%), followed by LinkedIn, X (Twitter), and Facebook (17% each). In terms of mental health, the majority of respondents were in the unhealthy category (87%).

Based on As presented in Table 2, the Chi-square analysis indicated that daily screen time was significantly associated with mental health status ($p < 0.001$). Respondents with high daily screen time showed a substantially higher proportion of unhealthy mental health compared to those with moderate and low screen time. Similarly, sleep quality was significantly associated with mental health ($p < 0.001$). Respondents reporting poor sleep quality exhibited the highest proportion of unhealthy mental health, whereas those with fair and good sleep quality showed lower proportions. In addition, stress level was significantly related to mental health status ($p < 0.001$). Respondents with high stress levels had a markedly greater proportion of unhealthy mental health compared to respondents with moderate and low stress levels. In contrast, no statistically significant associations were observed between mental health and gender ($p = 0.544$), age ($p = 0.853$), physical activity ($p = 0.800$), days without social media use ($p = 0.508$), or type of social media platform used ($p = 0.551$). Therefore, these variables were not included in the subsequent multivariate analysis.

The multivariate logistic regression model demonstrated a good fit to the data, as indicated by the Hosmer–Lemeshow goodness-of-fit test ($\chi^2 = 2.473$; df = 8; $p = 0.963$), suggesting no significant difference between the observed and predicted values. Based on Table 3, the results of the logistic regression analysis show that sleep quality is the most dominant factor associated with mental health. Respondents with good sleep quality were approximately 5.56 times more likely to be in the healthy mental health category compared to respondents with poor sleep quality (OR = 5.559; 95% CI: 2.841–10.878; $p < 0.001$), after controlling for other variables in the model.

Table 1. Distribution of Respondent Characteristics Based on Demographic, Behavioral, and Mental Health Factors (n = 477)

Variable	Sub-Category	n	%
Gender	Male	248	52%
	Female	229	48%
	Sum	**477**	**100%**
Age	Adolescents	70	15%
	Young Adults	122	26%
	Adults	147	31%
	Older Adults	138	29%
	Sum	**477**	**100%**
Daily screen time	Low	35	7%
	Medium	245	51%
	High	197	41%
	Sum	**477**	**100%**
Sleep Quality	Poor	60	13%
	Fair	314	66%
	Good	103	22%
	Sum	**477**	**100%**
Stress Level	Low	10	2%
	Medium	208	44%
	High	259	54%
	Sum	**477**	**100%**
No Social Media Category	Never	46	10%
	Rarely	137	29%
	Sometimes	243	51%
	Often	51	11%

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Variable	Sub-Category	n	%
	Sum	**477**	**100%**
Physical Activity	None	41	9%
	Low	212	44%
	Moderate	185	39%
	High	39	8%
	Sum	**477**	**100%**
Types of Social Media	Facebook	80	17%
	Instagram	71	15%
	Linkedln	83	17%
	Tiktok	92	19%
	X (Twitter)	82	17%
	YouTube	69	14%
	Sum	**477**	**100%**
Mental Health	Healthy	60	13%
	Unhealthy	417	87%
	Sum	**477**	**100%**

Source: Secondary data, processed by researchers (2026).

Table 2. Analysis of the Relationship between Demographic Factors and Behavior with Mental Health (Chi-Square Test)

Variable	**Subcategory**	**Mental Health**		**Sum**	***df***	***p-value***
		Healthy	**Unhealthy**			
Gender	Male	29	219	248	1	0.544
		11,70%	88,30%	100,00%		
	Female	31	198	229		
		13,50%	86,50%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
Age	Adolescents	11	59	70	3	0.853
		15,70%	84,30%	100,00%		
	Young Adults	14	108	122		

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		11,50%	88,50%	100,00%		
	Adults	18	129	147		
		12,20%	87,80%	100,00%		
	Older Adults	17	121	138		
		12,30%	87,70%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
Daily screen time	Low	0	35	35	2	**0.000**
		0,00%	100,00%	100,00%		
	Medium	3	242	245		
		1,20%	98,80%	100,00%		
	High	57	140	197		
		28,90%	71,10%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
Sleep Quality	Poor	31	29	60	2	**0.000**
		51,70%	48,30%	100,00%		
	Fair	29	285	314		
		9,20%	90,80%	100,00%		
	Good	0	103	103		
		0,00%	100,00%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
Stress Level	Low Low	0	10	10	2	**0.000**
		0,00%	100,00%	100,00%		
	Medium	2	206	208		
		1,00%	99,00%	100,00%		
	High	58	201	259		
		22,40%	77,60%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		

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Physical Activity	None	5	36	41	3	0.800
		12,20%	87,80%	100,00%		
	Low	27	185	212		
		12,70%	87,30%	100,00%		
	Moderate	25	160	185		
		13,50%	86,50%	100,00%		
	High	3	36	39		
		7,70%	92,30%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
No Social Media Category	Never	9	37	46	3	0.508
		19,57%	80,43%	100,00%		
	Rarely	17	120	137		
		12,41%	87,59%	100,00%		
	Sometimes	28	215	243		
		11,52%	88,48%	100,00%		
	Often	6	45	51		
		11,76%	88,24%	100,00%		
Sum		**60**	**417**	**477**		
		12,60%	**87,40%**	**100,00%**		
Types of Social Media	Facebook	9	71	80	5	0.551
		11,30%	88,80%	100,00%		
	Instagram	13	58	71		
		18,30%	81,70%	100,00%		
	Linkedln	7	76	83		
		8,40%	91,60%	100,00%		
	Tiktok	12	80	92		
		13,00%	87,00%	100,00%		
	X (Twitter)	9	73	82		
		11,00%	89,00%	100,00%		
	YouTube	10	59	69		

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	14,50%	85,50%	100,00%
Sum	**60**	**417**	**477**
	12,60%	**87,40%**	**100,00%**

Source: Secondary data, processed by researchers (2026).

Table 3. Multivariate Analysis of Logistic Regression of Behavioral and Psychosocial Factors on Mental Health

Variables in the Equation

Variable	**B**	**S.E.**	**Wald**	**df**	***Sig.***	**Exp(B)**	**95% C.I.for EXP(B)**	
							Lower	**Upper**
Daily screen time	-2,238	0,629	12,660	1	0,000	0,107	0,031	0,366
Sleep Quality	1,715	0,342	25,089	1	0,000	5,559	2,841	10,878
Stress Level	-1,874	0,767	5,976	1	0,015	0,154	0,034	0,690
Constant	**10,216**	**2,758**	**13,722**	**1**	**0,000**	**27324,886**		

Source: Secondary data, processed by researchers (2026).

DISCUSSION

Three factors emerged as significant predictors of mental health among social media users: screen time, sleep quality, and stress levels. But they don't matter equally. Sleep quality dominated the model, exerting roughly five times more influence on mental wellbeing than the other factors combined. Respondents with good sleep were 5.6 times more likely to report healthy mental wellbeing than those who slept poorly, even after accounting for screen time and stress. This hierarchy matters because it suggests where interventions should focus—and challenges common assumptions about what's actually harming mental health in the digital age.

The dominance of sleep quality aligns with established neuroscience: sleep serves as the brain's primary recovery mechanism, consolidating memories, regulating emotions, and restoring neuroendocrine balance (Dagani et al., 2024). When sleep falters, everything downstream suffers. The hypothalamic-pituitary-adrenal axis becomes dysregulated. Emotional reactivity increases. Coping capacity diminishes. What makes this finding particularly relevant is its biopsychosocial context—sleep doesn't just affect mood, it fundamentally shapes how we process stress, engage with others, and respond to daily challenges (State, 2025). Poor sleep creates a cascade: reduced emotional regulation leads to heightened stress reactivity, which further disrupts sleep, perpetuating a downward spiral. Our results suggest that breaking this cycle through sleep interventions could yield broader mental health benefits than interventions targeting screen time or stress management alone.

Screen time remained significantly associated with mental health even after controlling for sleep and stress, supporting displacement theory: hours spent scrolling replace activities that build psychological resilience—face-to-face conversation, physical movement, unstructured thinking time (Lo et al., 2025). The relationship isn't simply about duration, though. Late-night screen use disrupts circadian rhythms through exposure to blue light, creating a direct pathway to the sleep problems we've identified as paramount (Pieh et al., 2025). Previous research has documented associations between excessive screen use and psychological distress (Nakshine et al., 2022; Wang et al., 2023). Our contribution is showing that this relationship persists even when we account for sleep quality—suggesting that screen time harms mental health through multiple mechanisms, not just sleep disruption. This has practical implications: reducing evening screen time might improve mental health, both directly by reducing displacement and indirectly by improving sleep.

Stress levels showed significant associations with mental health, consistent with the stress-diathesis model (Bremner et al., 2020). Chronic stress depletes psychological resources and dysregulates the HPA axis, making individuals more vulnerable to mental health problems. However, stress proved less influential than sleep quality in our model. This doesn't diminish stress as a concern—instead, it suggests that sleep may mediate some of stress's mental health effects. People under high stress who sleep well may fare better than those whose stress disrupts their rest.

The null findings deserve equal attention. Age, gender, physical activity, days without social media, and platform choice showed no significant relationship with mental health. These non-findings challenge common assumptions. We often assume young people suffer more from social media, or that Instagram harms mental health more than LinkedIn. Our data don't support these generalizations. What explains these null results? Possibly, mental health effects stem more from how people use social media than from who they are or which platform they choose. A 50-year-old scrolling TikTok at 2 AM while stressed faces similar risks as a 20-year-old doing the same. The intensity and quality of engagement matter more than demographic categories. This interpretation aligns with recent calls to move beyond simplistic "screen time bad" narratives toward a more nuanced understanding of the complexities of digital life (Kirkbride et al., 2024). The lack of association with physical activity surprises, given established links between exercise and mental health. Perhaps our measure—exercise frequency per week—captured quantity rather than quality, or perhaps physical activity's mental health benefits operate through pathways such as stress reduction and improved sleep, which are already accounted for in our model.

These findings redirect intervention priorities. Public health campaigns often emphasize "unplug and exercise" or "take social media breaks." Our results suggest a different emphasis: sleep first. Programs that improve sleep hygiene—consistent bedtimes, dark quiet environments, pre-sleep routines—may deliver greater mental health returns than programs focused primarily on reducing screen time. That said, integrated approaches seem most promising. Reducing screen time supports better sleep, particularly when screens are eliminated from bedrooms and during evening hours. Stress management techniques complement both, as chronic stress disrupts sleep and drives escapist screen use. Rather than choosing between interventions, practitioners should sequence them strategically: establish sleep foundations, then address screen habits that undermine sleep, then build stress management skills that protect both (Agyapong-opoku et al., 2025; Rutter et al., 2021; Yang et al., 2025). This integrated approach also respects individual variation. Some people manage high screen time without mental health consequences because they protect their sleep. Others experience stress without deterioration because they maintain healthy sleep and screen habits. Interventions should assess all three factors and target the specific vulnerabilities each person faces rather than applying one-size-fits-all solutions.

CONCLUSION

This study concludes that behavioral and psychosocial factors play a more decisive role in the mental health of social media users than demographic factors. Daily screen time, sleep quality, and stress levels were significantly related to mental health ($p < 0.001$), with sleep quality emerging as the most dominant factor (OR = 5.559; 95% CI: 2.841-10.878). These findings confirm that mental health in the digital age is not only influenced by exposure to social media itself, but also by how individuals manage screen time, rest patterns, and responses to stress. Practically, these research results emphasize the importance of promotive and preventive approaches in public health that focus on three key areas: (1) promoting healthy sleep hygiene practices through education and behavioral interventions, (2) encouraging controlled screen time particularly during nighttime hours, and (3) strengthening stress management skills through accessible mental health support programs. Public health practitioners and policymakers should prioritize integrated interventions that address these interconnected factors rather than focusing on single-factor approaches.

LIMITATION

This study's limitations stem primarily from its reliance on secondary data. We had no control over how the original dataset was collected, the sampling methods used, or the populations included. The dataset documentation provides limited information about respondents' geographic locations, cultural contexts, or socioeconomic backgrounds—factors that are likely to shape both social media use and mental health outcomes. We cannot verify whether the sample represents broader populations or assess potential selection biases in the recruitment process. These constraints limit generalizability and require caution when applying findings to specific groups or settings.

The cross-sectional design prevents causal inference. We observed that poor sleep is associated with poor mental health, but we cannot determine the direction of causality. Does inadequate sleep harm mental wellbeing, or do mental health problems disrupt sleep? Both likely occur, creating bidirectional relationships our analysis cannot untangle. Similarly, high screen time might cause mental health deterioration, or people experiencing distress might seek refuge in digital spaces. Longitudinal data tracking individuals over time would clarify these temporal sequences, but we lack such information.

Measurement limitations also constrain interpretation. All variables were based on self-reports, introducing recall bias, social desirability bias, and subjective interpretation of response categories. Our mental health measure—a 1-10 happiness scale—captures subjective well-being but lacks the clinical precision of validated instruments such as the PHQ-9 or GAD-7. We cannot distinguish between normal mood variation and clinically significant mental health conditions. The dataset creator predetermined the categorization thresholds for screen time, sleep quality, and stress, which may not align with established clinical guidelines or validated cut-points used in the research literature.

Our model, despite controlling for multiple factors, inevitably omits variables that influence mental health. Socioeconomic status shapes access to resources that support wellbeing. Prior history of mental disorders affects vulnerability. Social support networks buffer against stress. Access to mental health services enables intervention. We accounted for none of these confounders, meaning observed associations may partly reflect unmeasured factors. Additionally, we excluded respondents who identified as gender "other" due to a small sample size—a decision that excludes valuable perspectives from already marginalized groups.

Future research should address these gaps through longitudinal designs using validated mental health instruments and comprehensive covariate assessment. Studies examining moderating factors—how social support, digital literacy, or coping skills alter the relationship between screen time and mental health—would deepen mechanistic understanding. Cross-cultural comparisons would test whether our findings generalize across contexts where social media plays different social roles. Most importantly, intervention trials testing whether improving sleep hygiene actually enhances mental health outcomes would move from correlation to causation, providing the evidence base needed for confident public health recommendations.

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