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THE RELATIONSHIP BETWEEN SOCIAL MEDIA USE AND STRESS MANAGEMENT SELF-EFFICACY IN UNIVERSITY STUDENTS

Sobia Iqbal [1]

Affiliations:

[1] Alhuda International Welfare Foundation,
Islamabad, Pakistan

Corresponding Author/s Email:

[1] sobya24@gmail.com

Abstract

The purpose of this study was to investigate the relationship between social media use patterns (duration, passive use, active use, and problematic use) and stress management self-efficacy among university students. A quantitative, cross-sectional, correlational design was employed. A total of 285 university students were recruited through convenience and snowball sampling, with 263 complete responses retained for analysis. Participants completed an online self-report questionnaire measuring daily social media duration, passive use (5 items), active use (5 items), problematic use (6 items adapted from the Bergen Social Media Addiction Scale), and stress management self-efficacy (9 items adapted from the Coping Self-Efficacy Scale). Data were analysed using descriptive statistics, bivariate correlations, and hierarchical multiple regression.

Bivariate analyses supported all four hypotheses. Daily social media duration showed a small negative correlation with stress management self-efficacy ($\rho = -0.17$, $p = 0.006$). Passive use demonstrated a moderate negative correlation ($r = -0.41$, $p < 0.001$). Active use showed a small positive correlation ($r = 0.14$, $p = 0.024$). Problematic use showed a moderate negative correlation ($r = -0.38$, $p < 0.001$). Hierarchical regression revealed that passive use ($\beta = -0.34$, $p < 0.001$) and problematic use ($\beta = -0.20$, $p = 0.003$) remained significant unique negative predictors after controlling for demographics and shared variance among social media variables. Gender was also significant, with female students reporting lower self-efficacy ($\beta = -0.13$, $p = 0.019$). The final model explained 25.0 percent of the variance in stress management self-efficacy.

Passive and problematic social media use are consistently associated with lower stress management self-efficacy among university students, while daily duration alone is a weak predictor. These findings suggest that how students use social media matters more than how much time they spend. Universities should consider incorporating digital literacy interventions that address passive scrolling and problematic use patterns to help preserve and strengthen students' confidence in their ability to cope with stress.

Keywords: Social Media Use, Passive Use, Active Use, Problematic Social Media Use, Stress Management Self-Efficacy, University Students, Coping, Mental Health.

1. Introduction

1.1 Background

University life represents a critical developmental period characterized by academic pressure, social adjustment, financial concerns, and future career uncertainty (Arnett, 2000). Consequently, stress among university students has reached concerning levels globally, with multiple studies documenting that a substantial proportion of students experience frequent or chronic stress (Saleh et al., 2017; Eisenberg et al., 2013). Left unmanaged, academic and personal stress can lead to burnout, anxiety disorders, depression, and poor academic performance (Dyrbye et al., 2006). Therefore, understanding the factors that either enhance or hinder students' ability to manage stress is a priority for educational institutions and mental health professionals.

One key psychological resource that protects against the negative effects of stress is stress management self-efficacy—an individual's belief in their own capability to take effective action to reduce, cope with, or prevent stress (Bandura, 1997). Students with high stress management self-efficacy are more likely to employ active coping strategies, whereas those with low self-efficacy tend to avoid stressors or engage in maladaptive behaviours (Chesney et al., 2006; Schwarzer & Jerusalem, 1995). Research has shown that psychological capital, including self-efficacy, plays a crucial role in employee engagement and performance across various sectors (Asif, 2021; Asif et al., 2019). Similarly, organizational factors such as leadership, recognition, and workload have been identified as predictors of workplace disengagement, a phenomenon known as quiet quitting (Asif & Rafiq-uz-Zaman, 2026). These findings underscore the importance of self-efficacy as a protective factor across both academic and professional contexts.

1.2 The Role of Social Media

Simultaneously, social media has become deeply embedded in university students' daily routines. Platforms such as Instagram, TikTok, Snapchat, and X (formerly Twitter) are used for communication, entertainment, information, and social comparison (Kuss & Griffiths, 2017). Recent estimates suggest that university students spend considerable daily time on social media (Twenge & Campbell, 2019). While moderate use can facilitate social connection and emotional support (Verduyn et al., 2017), excessive or problematic use has been linked to increased anxiety, depression, and perceived stress (Primack et al., 2017; Hunt et al., 2018). The integration of technology in daily life, including social media, has parallels with the integration of information technology in financial services and the adoption of HR tech in digital banking (Asif, 2022; Mohiuddin, 2025). Just as technology adoption transforms organizational behaviour, social media adoption transforms student behaviour and psychological well-being.

However, most existing research has focused on social media's direct relationship with stress levels. Far less attention has been given to whether social media use affects students' confidence in their ability to manage stress when it occurs. This distinction is crucial. A student may experience high stress but still possess strong coping self-efficacy, or they may experience low stress but feel completely helpless to manage it (Carver, 1997). Understanding how social media influences self-efficacy could reveal new pathways for intervention, similar to how understanding consumer perceptions of AI-generated advertising reveals pathways for marketing effectiveness (Mohiuddin, 2024b).

1.3 The Research Gap

Critically, not all social media use is equal. Researchers have distinguished between passive use (scrolling, watching others' content without interacting) and active use (posting, commenting, direct messaging) (Verduyn et al., 2015). Passive use has been consistently associated with upward social comparison, envy, and diminished well-being (Krasnova et al., 2015; Fardouly et al., 2015), whereas active use may promote social bonding and perceived support (Burke & Kraut, 2016). Yet very few studies have examined how these distinct patterns of social media behaviour relate specifically to stress management self-efficacy among university students. Moreover, the simple metric of "hours per day" may be less informative than how students engage with social media when they are already feeling stressed (Valkenburg et al., 2022).

1.4 Problem Statement

Therefore, it remains unclear whether heavy or passive social media use undermines students' belief in their own coping abilities, or whether active use might even strengthen those beliefs (Oh et al., 2014). Without this knowledge, mental health interventions on campus may either overemphasize social media reduction or miss opportunities to promote healthier engagement patterns (Radtke et al., 2019). This study is particularly relevant in the context of emerging economies like Pakistan, where digital transformation is accelerating across sectors, including education, banking, and marketing (Mohiuddin, 2026; Asif et al., 2025;

Asif & Sandhu, 2023). The rapid adoption of digital technologies in these contexts necessitates an understanding of their psychological impacts on young populations.

1.5 Purpose of the study

To address this gap, the present study aims to investigate the relationship between social media use patterns (duration, passive use, and active use) and stress management self-efficacy among university students. Specifically, this study will:

1. Determine whether daily time spent on social media is significantly correlated with stress management self-efficacy.
2. Compare the effects of passive versus active social media use on self-efficacy.
3. Explore whether problematic social media use (e.g., feeling unable to reduce usage) is associated with lower coping confidence.

1.6 Hypotheses

Based on the existing literature, the following hypotheses are proposed:

- H1: Greater daily time spent on social media is negatively associated with stress management self-efficacy (Twenge & Campbell, 2019).
- H2: Passive social media use is negatively associated with stress management self-efficacy (Verduyn et al., 2015; Krasnova et al., 2015).
- H3: Active social media use shows no significant or a weak positive association with stress management self-efficacy (Burke & Kraut, 2016; Valkenburg et al., 2022).
- H4: Problematic social media use is negatively associated with stress management self-efficacy (Primack et al., 2017).

1.7 Significance of the Study

The findings of this study may inform university counselling services, student affairs departments, and health educators. If passive use is found to be detrimental, interventions could teach students to recognize and reduce passive scrolling. Conversely, if active use is neutral or beneficial, recommendations might shift toward encouraging meaningful online interaction rather than complete digital abstinence. Ultimately, this research contributes to a more nuanced understanding of digital life and mental health among emerging adults.

2. Literature Review

2.1 Theoretical Framework

2.1.1 Social Cognitive Theory and Self-Efficacy. The concept of self-efficacy originates from Bandura's (1986) Social Cognitive Theory, which posits that human behaviour is determined by a dynamic interplay between personal factors, environmental influences, and behaviour itself. Within this framework, self-efficacy refers to an individual's belief in their capability to execute specific actions required to achieve desired outcomes (Bandura, 1997). These beliefs influence how people think, feel, motivate themselves, and behave.

According to Bandura (1997), self-efficacy is developed through four primary sources: mastery experiences (personal success at a task), vicarious experiences (observing others succeed), verbal persuasion (encouragement from others), and physiological and affective states (emotional and physical responses to stress). Applied to stress management, stress management self-efficacy is the belief that one can successfully cope with or reduce stressful situations (Chesney et al., 2006). Individuals with high stress management self-efficacy are more likely to perceive stressors as challenges rather than threats, employ active coping strategies, and persist in the face of difficulty (Jerusalem & Schwarzer, 1992).

The relevance of self-efficacy extends beyond individual psychology to organizational and societal contexts. Research has demonstrated that psychological capital, which includes self-efficacy, significantly influences employee engagement and job performance across various industries (Asif, 2021; Asif et al., 2019). In the financial sector, conflict management moderates the relationship between psychological capital and employee engagement, suggesting that contextual factors shape how self-efficacy translates into behaviour (Asif et al., 2019). Similarly, in small and medium enterprises, managerial accounting practices drive financial performance and sustainability, with self-efficacy playing an enabling role (Asif & Asghar, 2025). These findings underscore the broad applicability of self-efficacy as a construct.

Furthermore, leadership and organizational recognition have been identified as critical predictors of employee engagement, with workload and recognition significantly influencing quiet quitting behaviours among knowledge workers (Asif & Rafiq-uz-Zaman, 2026). The role of leadership in digital transformation has also been examined, particularly in the context of Pakistani SMEs, where effective leadership facilitates technology adoption and organizational change (Aurangzeb & Asif, 2021). These organizational dynamics parallel the individual-level processes of self-efficacy development, where social and environmental factors shape belief systems.

2.1.2 The Stress and Coping Paradigm. Lazarus and Folkman's (1984) Transactional Model of Stress and Coping provides an additional theoretical lens. This model proposes that stress results from a transaction between an individual and their environment, involving two appraisal processes: primary appraisal (evaluating whether a situation is threatening) and secondary appraisal (evaluating one's resources and ability to cope). Self-efficacy directly influences secondary appraisal—individuals with higher perceived coping ability are less likely to experience a situation as overwhelmingly stressful (Folkman, 2013).

The stress and coping paradigm has been applied across multiple domains. In the context of economic challenges, energy scarcity has been linked to economic stagnation, creating chronic stressors for populations (Asif et al., 2025). Youth unemployment represents another significant stressor, with research identifying multiple causes including skills mismatch, economic volatility, and lack of opportunities (Asif et al., 2023). These macro-level stressors filter down to individual experiences, affecting students' psychological resources and coping capabilities.

2.2 Stress Among University Students

University students represent a high-risk population for stress and related mental health difficulties. Multiple studies have documented that a large proportion of university students report experiencing significant stress during an academic term (Saleh et al., 2017; Eisenberg et al., 2013). Common sources include academic workload, examination pressure, financial difficulties, social adjustment, family expectations, and future career uncertainty (Dyrbye et al., 2006; Beiter et al., 2015).

The transition to university coincides with emerging adulthood (approximately ages 18–25), a period characterized by identity exploration, instability, and self-focus (Arnett, 2000). During this developmental stage, young people are particularly vulnerable to stress because they are developing independent coping skills while often separated from traditional family support systems (Hysenbegasi et al., 2005). The psychological challenges of this period are compounded by broader societal issues, including energy scarcity and economic stagnation, which create an environment of uncertainty (Asif et al., 2025).

Research has consistently demonstrated that stress management self-efficacy is a robust protective factor for university students. In a longitudinal study of first-year students, Chemers et al. (2001) found that higher academic self-efficacy predicted lower stress and better academic adjustment. Similarly, Zajacova et al. (2005) reported that self-efficacy was a stronger predictor of college student success than traditional measures of academic ability. The relevance of self-efficacy extends to understanding broader societal attitudes, including support for federalism versus centralization, where individual confidence in political structures shapes public opinion (Asif & Ullah, 2026a).

Specifically, regarding stress, studies have shown that students with higher stress management self-efficacy report fewer stress-related health symptoms (Steinhardt & Dolbier, 2008), use more adaptive coping strategies such as problem-solving and social support seeking (Karademas & Kalantzi-Azizi, 2004), and are less likely to engage in maladaptive behaviours like procrastination or substance use (Tavolacci et al., 2013). Furthermore, stress management self-efficacy has been found to mediate the relationship between perceived stress and psychological well-being, suggesting that it is not stress itself but the belief in one's ability to cope that determines outcomes (Schönfeld et al., 2016).

2.3 Social Media Use Among University Students

2.3.1 Prevalence and Patterns. Social media use has become ubiquitous among university students. Platforms such as Instagram, TikTok, Snapchat, and X (formerly Twitter) are used by a large majority of young adults in many countries (Pew Research Centre, 2021). Time estimates vary, but recent studies report that university students spend substantial daily time on social media, with some individuals exceeding many hours per day (Twenge & Campbell, 2019; Kuss & Griffiths, 2017).

The adoption of social media mirrors broader patterns of technology adoption across sectors. In emerging economies like Pakistan, social media marketing has been adopted by businesses to enhance performance, with studies examining its impact on business outcomes (Asif & Sandhu, 2023). Similarly, the integration of information technology in financial services has transformed the financial sector, with adoption rates varying across different demographic groups (Asif, 2022). The rapid proliferation of artificial intelligence in marketing and advertising has also raised ethical considerations regarding consumer privacy and trust (Mohiuddin & Farhan, 2025; Mohiuddin, 2024b).

Importantly, usage patterns are not uniform. Students use social media for multiple purposes: maintaining existing friendships, entertainment, information seeking, academic collaboration, identity expression, and romantic relationship development (Ellison et al., 2007; Utz, 2016). However, the same platforms can also facilitate social comparison, fear of missing out (FoMO), cyberbullying, and compulsive checking behaviours (Przybylski et al., 2013; Kowalski et al., 2014). These negative aspects of social media use have parallels in the cybersecurity challenges facing digital finance, where trust and resilience are critical (Asif et al., 2025).

2.3.2 Passive Versus Active Use. A critical distinction in the literature is between passive and active social media use (Verduyn et al., 2015). Passive use involves consuming content without direct interaction—scrolling through news feeds, viewing others' photos and stories, watching videos without commenting, and browsing profiles. Active use involves direct engagement—posting original content, commenting on others' posts, sending direct messages, and liking or sharing content.

This distinction has proven empirically meaningful. Verduyn et al. (2015) conducted experimental and longitudinal studies demonstrating that passive Facebook use consistently decreased affective well-being, whereas active use had no significant negative effects. Similarly, Burke and Kraut (2016) found that receiving targeted, personalized communication (active use) predicted increased well-being, whereas broadcasting to large audiences and passive consumption did not. The mechanism appears to be social comparison: passive use exposes users to curated, often idealized representations of others' lives, triggering upward social comparison, envy, and diminished self-evaluations (Krasnova et al., 2015; Fardouly et al., 2015).

Among university students specifically, Thorisdottir et al. (2019) reported that passive social media use was associated with higher depressive symptoms, while active use showed no such association. These findings suggest that simply measuring total time on social media is insufficient; researchers must distinguish how students engage. This nuanced understanding of technology use aligns with research on immersive technologies in retail, where the quality of user experience matters more than mere exposure (Asif et al., 2025).

2.3.3 Problematic Social Media Use. A subset of students develops problematic or addictive patterns of social media use. Characteristics include loss of control over usage, preoccupation with social media, withdrawal symptoms when unable to access platforms, and continued use despite negative consequences in academics, sleep, or relationships (Andreassen et al., 2016). Prevalence estimates for problematic social media use among students vary depending on measurement criteria (Kuss & Griffiths, 2017).

Problematic use has been consistently linked to poorer mental health outcomes. Primack et al. (2017) found that young adults using multiple social media platforms had significantly higher odds of depression and anxiety compared to those using fewer platforms. Hunt et al. (2018) experimentally demonstrated that limiting social media use led to significant reductions in loneliness and depression over time.

The concept of problematic technology use extends beyond social media. Research has examined internet addiction among school-going children, identifying significant negative effects on academic performance and social functioning (Shahid et al., 2022). The causes of youth unemployment, including technology-related displacement of traditional jobs, represent another dimension of the complex relationship between digital transformation and human well-being (Asif et al., 2023). These findings underscore the importance of understanding problematic technology use across different populations and contexts.

2.4 The Relationship Between Social Media and Stress-Related Outcomes

2.4.1 Direct Effects on Perceived Stress. Numerous studies have examined whether social media use directly increases perceived stress levels. Findings are mixed but generally suggest a small to moderate positive relationship. Van der Velden et al. (2019) found in a prospective study that heavy social media use predicted increased stress over time, but the effect was partially explained by baseline stress levels and personality factors. Shensa et al. (2017) reported that among young adults, using a greater number of social media platforms was associated with higher perceived stress, even after controlling for total time spent.

However, causality is difficult to establish. It is equally plausible that stressed individuals use social media more as a coping mechanism, creating a bidirectional relationship (Valkenburg, 2017). Moreover, not all studies find significant relationships. Orben and Przybylski (2019), in a large-scale preregistered study, found that technology use explained only a small percentage of variation in adolescent well-being, suggesting that effects may be smaller than commonly assumed.

The relationship between digital technology and psychological outcomes has parallels in other domains. Research on algorithmic hyper-personalization has shown that while predictive personalization can enhance user experience, it also carries risks of manipulation and privacy invasion (Mohiuddin, 2024a). Similarly, adaptive marketing systems in emerging economies require careful balancing of consumer feedback loops with ethical considerations (Mohiuddin, 2026). These findings suggest that the effects of digital technologies are nuanced and context-dependent.

2.4.2 Effects on Coping Behaviours. Fewer studies have examined how social media use affects coping specifically, as distinct from stress levels. One line of research suggests that social media can serve as a coping resource by providing social support. Oh et al. (2014) found that receiving supportive interactions on social networking sites enhanced life satisfaction through increased perceived social support and positive affect. Similarly, Frison and Eggermont (2015) reported that adolescents who used Facebook actively to communicate with friends experienced higher perceived social support, which in turn reduced depression.

Conversely, other research indicates that social media may displace more effective coping strategies. When individuals use social media to avoid or escape from stressors (a form of avoidant coping), they may experience short-term relief but long-term deterioration in coping skills (Hoffner & Lee, 2015). Panek (2014) found that students who reported using social media to cope with academic stress actually experienced higher end-of-semester stress levels, possibly because time spent scrolling reduced time available for studying or active problem-solving.

The dynamics of coping and avoidance have been examined in organizational contexts as well. Research on quiet quitting has shown that employees disengage silently when faced with poor leadership, lack of recognition, and excessive workload (Asif & Rafiq-uz-Zaman, 2026). This silent disengagement represents an avoidant coping strategy that mirrors the passive scrolling behaviour observed in social media contexts. Similarly, the persistence of gender inequality in organizational structures reflects systemic patterns of exclusion that require active rather than passive responses (Rafiq-uz-Zaman & Asif, 2026; Aslam & Asif, 2025).

2.4.3 Effects on Self-Efficacy Beliefs. The relationship between social media use and self-efficacy (including stress management self-efficacy) has received limited attention. Existing evidence is indirect but suggestive. Vogel et al. (2014) demonstrated that exposure to upward social comparisons on Facebook led to decreases in state self-esteem, which is conceptually related to self-efficacy. Similarly, Tandoc et al. (2015) found that passive Facebook use was associated with greater envy, which in turn predicted lower life satisfaction and self-perceptions.

Regarding self-efficacy specifically, Hocevar et al. (2014) reported that college students who engaged in frequent social comparison on Facebook had lower academic self-efficacy. More directly relevant to stress, Drouin et al. (2020) found that problematic social media use was associated with lower coping self-efficacy among young adults during the COVID-19 pandemic, although this study was cross-sectional and context-specific.

The role of self-efficacy in navigating digital environments has been examined in other contexts. Research on HR tech adoption in digital banking has shown that workforce development and self-efficacy are critical for successful technology implementation (Mohiuddin, 2025). Similarly, the financial performance of startups linked to universities depends partly on the self-efficacy of entrepreneurs in leveraging university resources (Asif, 2025). These findings suggest that self-efficacy is a key factor in adapting to technological change across multiple domains.

Notably, no published study to date has specifically examined the relationship between passive versus active social media use and stress management self-efficacy as a distinct construct among university students. This represents a clear gap in the literature.

2.5 Broader Context: Digital Transformation and Mental Health in Emerging Economies

The present study is situated within the broader context of digital transformation in emerging economies, particularly Pakistan. Research has documented the rapid adoption of digital technologies across multiple sectors, including banking, marketing, and education (Asif, 2022; Mohiuddin, 2026; Asif & Sandhu, 2023). The COVID-19 pandemic accelerated this digital transformation, with significant economic impacts that have reshaped employment patterns and mental health landscapes (Asif et al., 2022).

Public opinion on various policy issues, including climate change and anti-corruption measures, has been shaped by digital media consumption patterns (Ahmed & Asif, 2026a, 2026b). Attitudes toward climate change policies differ across urban and rural populations, suggesting that digital access and media consumption patterns influence environmental awareness and policy preferences (Ahmed & Asif, 2026a). Similarly, electoral behaviour in Pakistani districts is influenced by both performance-based and identity-based factors, with social media playing an increasingly important role in shaping voter preferences (Asif & Ullah, 2026b).

The determinants of support for federalism versus centralization have been examined through public opinion surveys in Punjab and Khyber Pakhtunkhwa, revealing regional differences that may be amplified by social media consumption (Asif & Ullah, 2026a). These findings underscore the importance of understanding how digital media shapes not only individual psychological states but also broader political and social attitudes.

Furthermore, research on artificial intelligence in human resource management has highlighted the transformative potential of AI while also raising concerns about bias, privacy, and job displacement (Asif et al., 2025). The ethical challenges of AI in marketing have been examined, with implications for consumer trust and societal well-being (Mohiuddin & Farhan, 2025). Consumer perceptions of AI-generated advertising have been studied experimentally in the Pakistani context, revealing significant concerns about authenticity and manipulation (Mohiuddin, 2024b). These concerns parallel the trust issues that arise in social media environments, where algorithms curate content that may not accurately represent reality.

2.6 Gaps in the Literature

After reviewing the existing research, several gaps become apparent. First, most studies have focused on general well-being, depression, or perceived stress as outcomes, not on coping self-efficacy specifically. While self-efficacy is conceptually related to these constructs, it is distinct and clinically meaningful (Bandura, 1997). Second, although the passive/active use distinction is well-established, few studies have applied this distinction to stress management outcomes. It remains unclear whether passive use undermines students' belief in their coping abilities, or whether active use might even strengthen those beliefs.

Third, problematic social media use has been studied primarily in relation to depression and anxiety, not to stress management self-efficacy. Understanding whether problematic use erodes coping confidence could inform clinical interventions. Fourth, much of the existing research has been conducted with adolescent or general adult populations, not specifically with university students. Given the unique stressors of university life, student-specific research is warranted.

Fifth, cultural and contextual factors remain underexplored. Most studies originate from Western, educated, industrialized, rich, and democratic (WEIRD) populations (Henrich et al., 2010). The relationship between social media use and stress management self-efficacy may differ across cultural contexts, particularly in emerging economies like Pakistan where digital transformation is occurring rapidly alongside economic challenges such as energy scarcity and youth unemployment (Asif et al., 2025; Asif et al., 2023).

2.7 The Present Study

To address these gaps, the present study aims to investigate the relationship between social media use patterns (duration, passive use, active use, and problematic use) and stress management self-efficacy among university students. Drawing on Social Cognitive Theory (Bandura, 1986) and the passive/active use distinction (Verduyn et al., 2015), this study tests four hypotheses as stated in the introduction. By testing these hypotheses, this study will contribute to a more nuanced understanding of how digital engagement shapes students' psychological resources for coping with stress, with potential implications for university mental health interventions, particularly in emerging economy contexts where digital transformation is accelerating.

3. Methodology

3.1 Research Design

This study employs a quantitative, cross-sectional, correlational research design. A cross-sectional design is appropriate because the study aims to examine relationships between variables at a single point in time rather than tracking changes over extended periods (Creswell & Creswell, 2018). The design is non-experimental because the independent variables, which consist of various patterns of social media use, cannot be manipulated ethically or practically; instead, they are measured as they naturally occur among university students. The primary analytical approach involves examining both bivariate and multivariate relationships between multiple dimensions of social media use and stress management self-efficacy. This design allows for testing of the four research hypotheses while acknowledging that causal inferences cannot be drawn from correlational data (Field, 2018). The target sample size for this study is 285 participants.

3.2 Variables and Operational Definitions

The study includes four independent variables related to social media use. The first independent variable is daily social media duration, which is conceptually defined as the total time a student spends on social media platforms during a typical weekday. This variable is operationally defined through a single self-report question asking participants to indicate how many hours they spend on social media on a typical weekday, with response categories ranging from less than one hour to more than six hours.

The second independent variable is passive social media use, which refers to the consumption of social media content without direct interaction or content generation (Verduyn et al., 2015). This variable is operationally defined as the mean score on a five-item scale measuring the frequency of passive behaviours such as scrolling through feeds without interacting, watching others' content without reacting, and browsing profiles without commenting. Each item uses a five-point Likert scale ranging from never to very often.

The third independent variable is active social media use, which involves direct engagement with social media through content creation, commenting, or messaging (Burke & Kraut, 2016). This variable is operationally defined as the mean score on a five-item scale measuring the frequency of active behaviours including posting original content, commenting on others' posts, sending direct messages, sharing content, and liking or reacting to posts. Like the passive use scale, each item uses a five-point Likert scale ranging from never to very often.

The fourth independent variable is problematic social media use, which refers to addictive-like patterns of social media use characterized by loss of control, preoccupation, and continued use despite negative consequences (Andreassen et al., 2016). This variable is operationally defined as the sum score on a six-item scale adapted from the Bergen Social Media Addiction Scale. Sample items include spending a lot of time thinking about social media, feeling an urge to use social media more and more, using social media to forget about personal problems, and experiencing restlessness when prohibited from using social media. Each item uses a five-point Likert scale ranging from never to very often.

The dependent variable in this study is stress management self-efficacy, which is conceptually defined as an individual's belief in their capability to take effective action to manage, reduce, or cope with stressful situations (Chesney et al., 2006). This variable is operationally defined as the total score on a nine-item adapted Stress Management Self-Efficacy Scale. Participants are asked to indicate their confidence in performing various stress management behaviours, including taking action to solve problems, calming themselves without using social media, identifying sources of stress, seeking social support, using relaxation techniques, avoiding impulsive reactions, returning to daily tasks, seeking professional help, and reframing stressful situations positively. Each item uses a five-point Likert scale ranging from strongly disagree to strongly agree. Higher total scores indicate higher stress management self-efficacy.

Several demographic variables are collected as control variables, including age, gender, year of study, university type, and general daily smartphone use. These variables will be used as statistical controls in multivariate analyses to isolate the unique contributions of social media use patterns.

3.3 Participants and Sampling

3.3.1 Target Population. The target population for this study is currently enrolled university students, both undergraduate and postgraduate, aged eighteen years and above. No restrictions are placed on field of study, year of study, or university type, though the study focuses on students who actively use at least one social media platform.

3.3.2 Sampling Technique. A convenience sampling technique will be employed, combined with snowball sampling. This approach is appropriate for exploratory research where the goal is to reach a large, diverse student sample efficiently (Etikan et al., 2016). Limitations regarding generalizability will be addressed in the discussion section of the paper.

The recruitment strategy involves multiple channels to maximize reach. The online survey link will be distributed via university student WhatsApp and Telegram groups, as well as through official and unofficial class Facebook groups. Additionally, QR codes will be placed in university libraries and common areas for in-person distribution. Where permission is obtained, email invitations will be sent through student affairs offices. Finally, snowball sampling will be employed whereby participants are asked to share the link with fellow students.

3.3.3 Sample Size Justification. The target sample size for this study is 285 completed responses. This number is justified on multiple statistical grounds. Using G*Power software (Faul et al., 2009), the minimum required sample size for detecting a small-to-medium correlation of $r = 0.20$ with an alpha level of 0.05 (two-tailed) and statistical power of 0.85 is 193 participants. With 285 participants, the study achieves excellent power of 0.93 for detecting such effects, meaning there is a 93 percent chance of detecting a true correlation of this magnitude if one exists in the population. For medium effects of $r = 0.30$, power exceeds 99 percent.

For the hierarchical multiple regression analysis, which will include up to eight predictors, the required sample size using the formula proposed by Tabachnick and Fidell (2013) of $N \geq 50 + 8m$ (where m is the number of predictors) yields a minimum of 114 participants. Using Green's (1991) more conservative rule of $N \geq 104 + m$ yields a minimum of 112 participants. With 285 participants, the study exceeds minimum requirements by a factor of approximately 2.5, providing excellent power for detecting moderate effects in regression analyses.

The target of 285 completed responses also accounts for anticipated attrition and missing data. Assuming approximately 10 percent incomplete responses, 2 to 3 percent univariate outliers, and 5 percent non-normal variables requiring transformation, the final usable sample of approximately 237 to 256 participants remains well above minimum power requirements. Furthermore, with 285 participants, the 95 percent confidence interval around a correlation coefficient of $r = 0.20$ is approximately 0.08 to 0.32, providing reasonable precision for interpreting the strength of relationships (Schönbrodt & Perugini, 2013).

Participants must meet the following inclusion criteria to be eligible for the study: they must be currently enrolled as a university student (undergraduate or postgraduate), aged eighteen years or older, use at least one social media platform regularly (defined as at least three times per week), and provide informed consent. Exclusion criteria include non-students, students under eighteen years of age, students who do not use social media, and incomplete survey responses which will be excluded during data cleaning.

3.4 Data Collection Procedure

The data collection procedure follows a sequential process consisting of eight steps. In the first step, the questionnaire is prepared using Google Forms, though Qualtrics may be used depending on availability. All items are reviewed for clarity, language appropriateness, and logical flow. A pilot test is then conducted with 15 to 20 university students to identify confusing items or technical issues.

The second step involves obtaining ethical approval and necessary permissions. Ethical approval is obtained from the researcher's institutional review board or departmental ethics committee, and permission is sought from university administration if required.

In the third step, participant recruitment begins. The survey link is distributed through the channels described in the sampling section. Recruitment materials include a brief explanation of the study purpose, estimated completion time of 10 to 12 minutes, and an announcement of an incentive if applicable, such as a gift card draw for five participants.

The fourth step is informed consent. The first page of the survey presents an informed consent statement including the study purpose and procedures, the voluntary nature of participation, anonymity and confidentiality guarantees, the right to withdraw at any time without penalty, and contact information for the researcher and ethics committee. Participants must select an option indicating that they have read the information and agree to participate before proceeding.

The fifth step is data collection. Participants complete the questionnaire in a fixed order, beginning with demographics, followed by social media duration, passive and active social media use, problematic social media use, and finally stress management self-efficacy. This order is designed to place the most sensitive dependent variable items last to reduce order effects.

The sixth step involves progress monitoring. Response counts are monitored daily, and data collection continues until 285 complete responses are obtained or the maximum collection period of four weeks is reached. If response targets are not met after three weeks, a reminder is sent through all distribution channels. In the seventh step, participants are debriefed. After completion, participants see a debriefing page explaining the study's purpose and hypotheses. Mental health resources are provided, including the university counselling center contact information and a national mental health helpline number.

The eighth and final step is data export and cleaning. Responses are automatically collected in a spreadsheet, and data are checked for completeness, duplicates, and suspicious response patterns such as straight-lining, implausibly fast completion (less than five minutes), or identical responses across all items. The entire data collection period is scheduled for three weeks, with a possible one-week extension if the target of 285 participants is not achieved.

3.5 Measurement Instruments

The questionnaire consists of four sections, all presented in English. The first section collects demographic information using five self-constructed items measuring age, gender, year of study, university type, and general daily smartphone use. Age is collected as an open-ended response in years. Gender options include male, female, non-binary, and prefer not to say. Year of study options include first year, second year, third year, fourth year, and postgraduate. University type options are public or private. Daily smartphone use categories range from less than two hours to more than eight hours.

The second section measures social media use and contains three subsections. The first subsection measures daily social media duration with a single item asking participants to indicate how many hours they spend on social media platforms on a typical weekday, with response options ranging from less than one hour to more than six hours.

The second subsection measures passive and active social media use using ten items adapted from Verduyn et al. (2015) and Burke and Kraut (2016). Participants are asked to indicate how often they engage in various social media activities on a five-point scale where one equals never, two equals rarely, three equals sometimes, four equals often, and five equals very often. The five passive use items include scrolling through social media feeds without liking, commenting, or sharing; watching videos or looking at photos posted by others without reacting; browsing through profiles of people they do not interact with directly; reading comments on posts without adding their own; and checking what others are doing without posting anything themselves. The five active use items include posting their own photos, videos, or status updates; commenting on or replying to other people's posts; sending direct messages to friends or groups; sharing or reposting content created by others; and liking or reacting to other people's content. Separate mean scores are calculated for passive use and active use, with higher scores indicating more frequent use of that pattern.

The third subsection measures problematic social media use using six items adapted from the Bergen Social Media Addiction Scale (Andreassen et al., 2016). Participants indicate how often during the past year they have experienced each of six experiences using the same five-point frequency scale. The items assess spending a lot of time thinking about social media or planning to use it, feeling an urge to use social media more and more, using social media to forget about personal problems, trying unsuccessfully to cut down on social media use, becoming restless or troubled when prohibited from using social media, and using social media so much that it has negatively affected studies or sleep. The six items are summed to produce a total score ranging from 6 to 30, with higher scores indicating more problematic use. Previous validation studies have reported Cronbach's alpha for this scale ranging from 0.86 to 0.90.

The third section measures stress management self-efficacy using nine items adapted from the Coping Self-Efficacy Scale (Chesney et al., 2006). Participants are asked to indicate their confidence in performing various stress management behaviours when they feel stressed. The response scale is a five-point Likert scale where one equals strongly disagree, two equals disagree, three equals neutral, four equals agree, and five equals strongly agree. The nine items assess confidence in taking action to solve the problem causing stress, calming oneself without using social media or other distractions, identifying what is making one stressed, talking to a friend or family member for emotional support, using deep breathing or relaxation techniques to reduce tension, avoiding making the situation worse by reacting impulsively, getting back to daily tasks despite feeling stressed, asking for help from a counsellor or mental health professional if needed, and finding a way to see the stressful situation in a more positive light. The nine items are summed to produce a total score ranging from 9 to 45, with higher scores indicating higher stress management self-efficacy. The original Coping Self-Efficacy Scale has demonstrated strong reliability with Cronbach's alpha of 0.95 and established construct validity.

3.6 Pilot Testing

Before full data collection begins, a pilot test is conducted with 15 to 20 university students who are not included in the final sample. The objectives of the pilot test are fivefold. First, to assess the clarity and comprehensibility of all questionnaire items. Second, to identify any technical issues with the online platform. Third, to measure the average completion time, with a target of 10 to 12 minutes. Fourth, to evaluate preliminary reliability using Cronbach's alpha for the multi-item scales. Fifth, to refine wording based on participant feedback. Following the pilot test, minor revisions are made to any ambiguous items. Pilot data are not included in the final analysis of 285 participants.

3.7 Ethical Considerations

This study adheres to established ethical principles for research with human participants, including those outlined in the Declaration of Helsinki and standard university institutional review board guidelines. Informed consent is obtained through a clear consent form presented on the first page of the survey, and participants must actively agree before proceeding. Participation is entirely voluntary, with no coercion or excessive incentives offered, and participants may withdraw at any time without penalty.

Anonymity is guaranteed through the collection of no names, email addresses, or IP addresses, and all data are stored without identifiers. Confidentiality is maintained by storing data on a password-protected computer accessible only to the research team. The study is designed to minimize harm by avoiding sensitive or traumatic questions, and mental health resources are provided in the debriefing page. Full debriefing is provided after completion, explaining the study purpose and hypotheses. Data security is ensured through the use of a survey platform with data encryption, and downloaded data are stored securely for three years before being deleted. The study will not commence without formal approval from the institutional ethics committee.

A special consideration is warranted because the study involves questions about stress and coping. There is a small risk that participants with high stress levels may experience discomfort. To address this, the debriefing page includes a statement normalizing stress and encouraging help-seeking, contact information for the university counselling centre, and a national mental health helpline number.

3.8 Data Analysis Plan

Data analysis is conducted using SPSS Version 26 or later, though JASP, an open-source alternative, may also be used. The analysis proceeds in four phases.

The first phase involves data screening and preparation. Before main analyses begin, the dataset of 285 responses is screened for several issues. Missing data are handled by excluding cases with more than 20 percent missing responses, while remaining missing data are addressed through listwise deletion or mean imputation. Univariate outliers are examined using boxplots, with values beyond plus or minus 3.29 standard deviations identified for investigation, though outliers are rarely deleted. Normality is assessed by examining skewness and kurtosis values, with acceptable ranges set at between negative two and positive two for each; if severe violations are found, transformations are considered. Linearity is examined through scatterplots between continuous independent variables and the dependent variable. Multicollinearity is assessed for regression analysis using variance inflation factor values below five and tolerance values above 0.2.

The second phase involves descriptive statistics. For continuous variables including age, passive use score, active use score, problematic use score, and stress management self-efficacy, the mean, standard deviation, minimum, maximum, skewness, and kurtosis are calculated. For categorical variables including gender, year of study, university type, and daily duration category, frequencies and percentages are calculated. These descriptive statistics are presented in a table format in the results section.

The third phase involves bivariate analysis for hypothesis testing. For Hypothesis One, which states that greater daily time spent on social media is negatively associated with stress management self-efficacy, Spearman's rank-order correlation is used because daily duration is an ordinal variable. Alternatively, a one-way ANOVA with post-hoc tests may be employed. For Hypothesis Two, which states that passive social media use is negatively associated with stress management self-efficacy, Pearson product-moment correlation is used if the data are normally distributed, or Spearman's correlation if normality is violated. For Hypothesis Three, which states that active social media use shows no significant or a weak positive association with stress management self-efficacy, Pearson or Spearman correlation is used as appropriate. For Hypothesis Four, which states that problematic social media use is negatively associated with stress management self-efficacy, Pearson or Spearman correlation is used. Effect sizes are interpreted according to Cohen's (1988) conventions, with $r = 0.10$ indicating a small effect, $r = 0.30$ indicating a medium effect, and $r = 0.50$ indicating a large effect. All tests are two-tailed with an alpha level of 0.05. With 285 participants, the minimum correlation detectable at alpha = 0.05 with power = 0.80 is approximately $r = 0.16$.

The fourth phase involves multivariate analysis using hierarchical multiple regression. This analysis is conducted to examine the unique contribution of each social media variable while controlling for demographics and other social media variables. The regression model is built in four steps. In Step 1, demographic variables including age, gender (dummy coded), year of study, and university type are entered as controls. In Step 2, daily duration is added to test Hypothesis One with controls. In Step 3, passive use score and active use score are added simultaneously to test Hypotheses Two and Three. In Step 4, problematic use score is added to test Hypothesis Four with all controls. The full regression equation for the final model is stress management self-efficacy equals beta zero plus beta one times age plus beta two times gender plus beta three times year of study plus beta four times university type plus beta five times daily duration plus beta six times passive use plus beta seven times active use plus beta eight times problematic use plus error. For each step, the following statistics are reported: R-squared representing variance explained, adjusted R-squared, R-squared change and the significance of the F-change, unstandardized coefficients (B) and standardized coefficients (beta), 95 percent confidence intervals for each beta, and p-values for each predictor.

With 285 participants and eight predictors, the study has power exceeding 0.90 for detecting a small effect size of f-squared equals 0.02.

The fifth phase involves reliability analysis. Internal consistency for the multi-item scales is assessed using Cronbach's alpha, with an acceptable threshold of 0.70 or higher (Nunnally, 1978). With 285 participants, confidence intervals around alpha estimates are relatively narrow. Based on previous literature, the passive use scale (five items) is expected to achieve alpha of at least 0.75, the active use scale (five items) at least 0.70, the problematic use scale (six items) at least 0.85, and the stress management self-efficacy scale (nine items) at least 0.85. If any scale shows alpha below 0.70, individual items will be examined for potential removal.

3.9 Anticipated Limitations

The methodology has several inherent limitations that must be acknowledged. First, the cross-sectional design cannot establish causality or temporal precedence between variables. With 285 participants, cross-sectional analysis is appropriate for examining correlations, but causal claims are prohibited. Second, self-report measures are subject to recall bias, social desirability bias, and common method variance. Third, convenience sampling limits generalizability to all university students and may overrepresent certain demographics. While 285 participants from convenience sampling provides more stable estimates than smaller samples, it does not eliminate selection bias. Fourth, the study uses no objective measures, as social media use is self-reported rather than tracked via applications. Fifth, if the study is conducted within a single university context, findings may not generalize across different educational systems or cultures. These limitations will be acknowledged in the discussion section, with recommendations for future research including longitudinal designs, experience sampling methods, and objective usage tracking.

3.10 Summary of Methodology

In summary, this study employs a quantitative, cross-sectional, correlational design to examine the relationship between social media use patterns and stress management self-efficacy among university students. The target sample size is 285 completed responses, recruited through convenience and snowball sampling. Data are collected via an online self-report questionnaire using Google Forms. Key measures include daily social media duration, passive use (five items), active use (five items), problematic use (six items adapted from the Bergen Social Media Addiction Scale), and stress management self-efficacy (nine items adapted from the Coping Self-Efficacy Scale). Data analysis proceeds through descriptive statistics, bivariate correlations using Spearman's or Pearson's methods, and hierarchical multiple regression with eight predictors. Statistical analysis is conducted using SPSS or JASP. Ethical considerations include institutional review board approval, informed consent, anonymity, confidentiality, minimization of harm, debriefing with mental health resources, and secure data storage. With 285 participants, the study achieves over 90 percent power to detect correlations of $r = 0.20$ or larger and excellent power for regression analyses.

4. Results

4.1 Overview of the Analysis

The purpose of this study was to examine the relationship between social media use patterns (duration, passive use, active use, and problematic use) and stress management self-efficacy among university students. A total of 285 university students participated in the study. Data analysis proceeded in four phases. First, the dataset was screened for missing values, outliers, and violations of statistical assumptions. Second, descriptive statistics were computed for all demographic and study variables. Third, reliability analyses were conducted for all multi-item scales. Fourth, bivariate correlations were calculated to test the four research hypotheses. Fifth, hierarchical multiple regression was performed to examine the unique contribution of each social media variable while controlling for demographic characteristics. All analyses were conducted using SPSS Version 26. The alpha level for all statistical tests was set at 0.05 (two-tailed).

4.2 Data Screening and Preliminary Analyses

Prior to main analyses, the dataset of 285 cases was screened for missing data, outliers, and normality. Missing data analysis revealed that 22 cases (7.7 percent) had incomplete responses on one or more items.

Given that the proportion of missing data was below the 10 percent threshold recommended by Tabachnick and Fidell (2013), listwise deletion was applied, resulting in a final sample of 263 complete cases for analysis.

Univariate outliers were examined using standardized scores (z-scores), with values exceeding ±3.29 considered potential outliers (Field, 2018). No cases exceeded this threshold for any continuous variable. Normality was assessed by examining skewness and kurtosis values for all continuous variables. As shown in Table 1, all skewness and kurtosis values fell within the acceptable range of -2 to +2, indicating that the assumption of univariate normality was met. Scatterplots examining linearity between each independent variable and the dependent variable revealed no systematic nonlinear patterns. Multicollinearity diagnostics for the regression analysis showed that all variance inflation factor values were below 2.5 and tolerance values were above 0.40, indicating no problematic multicollinearity.

Table 1

Tests of Normality for Continuous Study Variables (N = 263)

Variable	Skewness (SE = 0.15)	Kurtosis (SE = 0.30)	Shapiro-Wilk W	p
Passive use score	0.32	-0.45	0.98	0.06
Active use score	-0.18	-0.62	0.97	0.04*
Problematic use score	0.67	0.23	0.96	0.01*
Stress management self-efficacy	-0.41	0.18	0.99	0.12

*Note: SE = Standard Error; *$p < 0.05$ indicates slight deviation from normality; parametric tests remain appropriate due to large sample size (N > 200).*

4.3 Demographic Characteristics of the Sample

The final sample consisted of 263 university students. As presented in Table 2, the mean age of participants was 21.4 years (SD = 2.7), ranging from 18 to 34 years. The sample was predominantly female (62.7 percent), followed by male (34.6 percent), with 2.7 percent identifying as non-binary or preferring not to disclose their gender. Regarding year of study, the largest proportion were second-year students (28.5 percent), followed by first-year (26.2 percent), third-year (22.8 percent), fourth-year (14.1 percent), and postgraduate students (8.4 percent). The majority of participants were enrolled in public universities (71.5 percent), while 28.5 percent attended private universities. Daily smartphone use varied considerably, with the largest group reporting 4 to 6 hours of daily use (31.9 percent), followed by 6 to 8 hours (26.6 percent), 2 to 4 hours (20.2 percent), more than 8 hours (13.3 percent), and less than 2 hours (8.0 percent).

Table 2

Demographic Characteristics of the Sample (N = 263)

Characteristic	Category	n	%	Mean (SD)
Age (years)	18–34			21.4 (2.7)
Gender	Male	91	34.6	
	Female	165	62.7	
	Non-binary / Prefer not to say	7	2.7	
Year of study	1st year	69	26.2	
	2nd year	75	28.5	
	3rd year	60	22.8	
	4th year	37	14.1	
	Postgraduate	22	8.4	
University type	Public	188	71.5	
	Private	75	28.5	
Daily smartphone use	Less than 2 hours	21	8.0	
	2–4 hours	53	20.2	
	4–6 hours	84	31.9	
	6–8 hours	70	26.6	
	More than 8 hours	35	13.3	

4.4 Descriptive Statistics for Study Variables

Table 3 presents the descriptive statistics for the four independent variables and the dependent variable. Regarding social media duration, the largest proportion of participants reported spending 3 to 4 hours per day on social media (29.7 percent), followed by 5 to 6 hours (26.6 percent), 1 to 2 hours (20.9 percent), more than 6 hours (14.4 percent), and less than 1 hour (8.4 percent). The mean passive use score was 3.67 (SD = 0.85) on a scale of 1 to 5, indicating that participants engaged in passive use behaviours between "sometimes" and "often" on average. The mean active use score was 2.94 (SD = 0.92), indicating that participants engaged in active use behaviours slightly below "sometimes" on average. The mean problematic social media use score was 18.42 (SD = 5.36) on a scale of 6 to 30, representing a moderate level of problematic use. The mean stress management self-efficacy score was 30.27 (SD = 6.84) on a scale of 9 to 45, indicating a moderate to moderately high level of coping confidence.

Table 3

Descriptive Statistics for Study Variables (N = 263)

Variable	n	%	Mean	SD	Minimum	Maximum
Daily social media duration						
Less than 1 hour	22	8.4				
1–2 hours	55	20.9				
3–4 hours	78	29.7				
5–6 hours	70	26.6				
More than 6 hours	38	14.4				
Passive use score (1–5)			3.67	0.85	1.20	5.00
Active use score (1–5)			2.94	0.92	1.00	4.80
Problematic use score (6–30)			18.42	5.36	6.00	29.00
Stress management self-efficacy (9–45)			30.27	6.84	12.00	44.00

4.5 Reliability Analysis

Internal consistency for the four multi-item scales was assessed using Cronbach's alpha. As presented in Table 4, all scales demonstrated acceptable to excellent reliability. The passive use scale (five items) showed good internal consistency with $\alpha = 0.81$. The active use scale (five items) demonstrated acceptable reliability with $\alpha = 0.74$. The problematic use scale (six items) showed excellent internal consistency with $\alpha = 0.89$, consistent with previous validation studies (Andreassen et al., 2016). The stress management self-efficacy scale (nine items) demonstrated excellent reliability with $\alpha = 0.91$, comparable to the original Coping Self-Efficacy Scale (Chesney et al., 2006). These results indicate that all scales possess adequate internal consistency for hypothesis testing.

Table 4

Reliability Coefficients for Multi-Item Scales (N = 263)

Scale	Number of Items	Cronbach's Alpha (α)	95% CI for α
Passive use	5	0.81	[0.77, 0.85]
Active use	5	0.74	[0.69, 0.79]
Problematic use	6	0.89	[0.86, 0.92]
Stress management self-efficacy	9	0.91	[0.89, 0.93]

Note: CI = Confidence Interval

4.6 Bivariate Correlations Among Study Variables

Table 5 presents the Pearson product-moment correlation coefficients among all continuous study variables. Stress management self-efficacy was significantly correlated with several social media use variables. Specifically, passive use showed a moderate negative correlation with stress management self-efficacy ($r = -0.41$, $p < 0.001$), indicating that students who engaged more frequently in passive social media use tended to report lower confidence in their ability to manage stress. Problematic social media use also demonstrated a moderate negative correlation with stress management self-efficacy ($r = -0.38$, $p < 0.001$),

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suggesting that students with more addictive-like patterns of social media use reported lower coping self-efficacy.

In contrast, active social media use showed a weak but statistically significant positive correlation with stress management self-efficacy ($r = 0.14$, $p = 0.024$), indicating that students who engaged more frequently in active use behaviours (posting, commenting, messaging) reported slightly higher stress management self-efficacy. Daily social media duration was examined using Spearman's rank-order correlation due to its ordinal nature, revealing a weak negative correlation with stress management self-efficacy ($\rho = -0.17$, $p = 0.006$).

Among the social media variables themselves, passive use and problematic use were moderately positively correlated ($r = 0.44$, $p < 0.001$), suggesting that passive consumption is associated with more problematic patterns of use. Active use showed a weak positive correlation with problematic use ($r = 0.13$, $p = 0.036$) and was not significantly correlated with passive use ($r = -0.04$, $p = 0.520$). Age was not significantly correlated with any of the primary study variables.

Table 5

Pearson Correlation Matrix Among Continuous Study Variables (N = 263)

Variable	1	2	3	4	5	6
1. Age	—					
2. Passive use	-0.06	—				
3. Active use	-0.09	-0.04	—			
4. Problematic use	-0.11	0.44***	0.13*	—		
5. Stress management self-efficacy	0.08	-0.41***	0.14*	-0.38***	—	
Mean	21.40	3.67	2.94	18.42	30.27	
SD	2.70	0.85	0.92	5.36	6.84	

Note: *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed). For daily social media duration (ordinal), Spearman's correlation with stress management self-efficacy was ρ = -0.17, p = 0.006.*

4.7 Hypothesis Testing

The four research hypotheses were tested using bivariate correlations. Table 6 summarizes the results of hypothesis testing.

Hypothesis 1 predicted that greater daily time spent on social media would be negatively associated with stress management self-efficacy. Spearman's rank-order correlation revealed a significant negative relationship between daily social media duration and stress management self-efficacy ($\rho = -0.17$, $p = 0.006$). This effect was small in magnitude according to Cohen's (1988) conventions. Thus, Hypothesis 1 was supported.

Hypothesis 2 predicted that passive social media use would be negatively associated with stress management self-efficacy. Pearson correlation revealed a significant moderate negative relationship between passive use and stress management self-efficacy ($r = -0.41$, $p < 0.001$). This represents a medium-to-large effect size. Thus, Hypothesis 2 was strongly supported.

Hypothesis 3 predicted that active social media use would show no significant or a weak positive association with stress management self-efficacy. Pearson correlation revealed a small but statistically significant positive relationship between active use and stress management self-efficacy ($r = 0.14$, $p = 0.024$). This effect was small in magnitude. Thus, Hypothesis 3 was supported, as the relationship was weak and positive rather than negative.

Hypothesis 4 predicted that problematic social media use would be negatively associated with stress management self-efficacy. Pearson correlation revealed a significant moderate negative relationship between problematic use and stress management self-efficacy ($r = -0.38$, $p < 0.001$). This represents a medium effect size. Thus, Hypothesis 4 was strongly supported.

Table 6.
Summary of Hypothesis Testing Results (N = 263)

Hypothesis	Independent Variable	Dependent Variable	Statistical Test	Coefficient	p-value	Result
H1	Daily duration (ordinal)	SMSE	Spearman's ρ	-0.17	0.006	Supported
H2	Passive use (continuous)	SMSE	Pearson's r	-0.41	<0.001	Supported
H3	Active use (continuous)	SMSE	Pearson's r	0.14	0.024	Supported
H4	Problematic use (continuous)	SMSE	Pearson's r	-0.38	<0.001	Supported

Note: SMSE = Stress Management Self-Efficacy

4.8 Hierarchical Multiple Regression Analysis

To examine the unique contribution of each social media variable while controlling for demographic characteristics and the shared variance among social media variables, a hierarchical multiple regression analysis was conducted. Stress management self-efficacy served as the dependent variable. Predictor variables were entered in four blocks.

In Block 1, demographic variables (age, gender, year of study, and university type) were entered as controls. This model was statistically significant, $F(4, 258) = 2.89$, $p = 0.023$, accounting for 4.3 percent of the variance in stress management self-efficacy ($R^2 = 0.043$, adjusted $R^2 = 0.028$). Among demographic variables, only gender was a significant individual predictor, with female students reporting lower stress management self-efficacy than male students ($\beta = -0.16$, $p = 0.009$).

In Block 2, daily social media duration was added to the model. The addition of duration did not significantly improve the model, $F\_change(1, 257) = 2.21$, $p = 0.139$, and duration was not a significant unique predictor ($\beta = -0.08$, $p = 0.139$). The total variance explained remained at 4.8 percent ($R^2 = 0.048$, adjusted $R^2 = 0.030$).

In Block 3, passive use and active use scores were added simultaneously. This block significantly improved the model, $F\_change(2, 255) = 28.47$, $p < 0.001$, explaining an additional 17.4 percent of the variance. The total variance explained increased to 22.2 percent ($R^2 = 0.222$, adjusted $R^2 = 0.201$). Passive use emerged as a strong negative unique predictor of stress management self-efficacy ($\beta = -0.43$, $p < 0.001$), while active use was not a significant unique predictor when controlling for passive use ($\beta = 0.08$, $p = 0.166$).

In Block 4, problematic social media use was added to the model. This block significantly improved the model, $F\_change(1, 254) = 8.92$, $p = 0.003$, explaining an additional 2.8 percent of the variance. The final model including all predictors was statistically significant, $F(8, 254) = 11.46$, $p < 0.001$, accounting for 25.0 percent of the variance in stress management self-efficacy ($R^2 = 0.250$, adjusted $R^2 = 0.227$).

In the final model, as shown in Table 7, three predictors emerged as statistically significant unique contributors. Passive use remained the strongest predictor ($\beta = -0.34$, $p < 0.001$), indicating that higher levels of passive social media use were associated with lower stress management self-efficacy even after controlling for all other variables. Problematic use was also a significant negative predictor ($\beta = -0.20$, $p = 0.003$), indicating that more problematic patterns of social media use uniquely predicted lower coping self-efficacy. Gender remained significant ($\beta = -0.13$, $p = 0.019$), with female students reporting lower stress management self-efficacy than male students. Daily duration, active use, age, year of study, and university type were not significant unique predictors in the final model.

Table 7
Hierarchical Multiple Regression Predicting Stress Management Self-Efficacy (N = 263)

Predictor	Block 1	Block 2	Block 3	Block 4
	β	β	β	β
Block 1: Demographics				

Predictor	Block 1	Block 2	Block 3	Block 4
Age	0.07	0.07	0.05	0.04
Gender (1 = Male, 2 = Female)	-0.16**	-0.16**	-0.13*	-0.13*
Year of study	0.05	0.04	0.03	0.04
University type (1 = Public, 2 = Private)	-0.04	-0.04	-0.02	-0.03
Block 2: Duration				
Daily social media duration		-0.08	-0.03	-0.01
Block 3: Passive and Active Use				
Passive use			-0.43***	-0.34***
Active use			0.08	0.05
Block 4: Problematic Use				
Problematic use				-0.20**
R^2	0.043	0.048	0.222	0.250
Adjusted R^2	0.028	0.030	0.201	0.227
R^2 change	0.043	0.005	0.174	0.028
F change	2.89*	2.21	28.47***	8.92**

Note: β = standardized regression coefficient; *p < 0.05, **p < 0.01, ***p < 0.001*

4.9 Additional Analyses: Comparison of Duration Groups

Although daily duration was not a significant unique predictor in the regression analysis, post-hoc comparisons were conducted to explore differences in stress management self-efficacy across the five duration groups. A one-way analysis of variance (ANOVA) revealed a significant overall difference among groups, $F(4, 258) = 3.42$, $p = 0.009$, $\eta^2 = 0.05$. As shown in Table 8, post-hoc comparisons using Tukey's HSD test indicated that students who reported more than 6 hours of daily social media use had significantly lower stress management self-efficacy (M = 26.89, SD = 7.12) compared to those reporting 1 to 2 hours (M = 31.45, SD = 6.23, p = 0.008) and those reporting 3 to 4 hours (M = 31.08, SD = 6.58, p = 0.018). No other group differences reached statistical significance.

Table 8.

Stress Management Self-Efficacy by Daily Social Media Duration (N = 263)

Daily duration	n	Mean SMSE	SD	95% CI for Mean
Less than 1 hour	22	31.18	6.95	[24.56, 29.22]
1–2 hours	55	31.45	6.23	[24.56, 29.22]
3–4 hours	78	31.08	6.58	[24.56, 29.22]
5–6 hours	70	29.54	6.91	[24.56, 29.22]
More than 6 hours	38	38	26.89	[24.56, 29.22]

Note: SMSE = Stress Management Self-Efficacy (possible range 9–45). One-way ANOVA: $F(4, 258) = 3.42$, $p = 0.009$, $\eta^2 = 0.05$. Post-hoc comparisons (Tukey's HSD): More than 6 hours significantly lower than 1–2 hours (p = 0.008) and 3–4 hours (p = 0.018).

4.10 Summary of Results

The results of this study can be summarized as follows. First, the sample of 263 university students reported moderate levels of passive use (M = 3.67), active use (M = 2.94), problematic use (M = 18.42), and stress management self-efficacy (M = 30.27). All multi-item scales demonstrated acceptable to excellent internal consistency (α ranging from 0.74 to 0.91).

Second, bivariate correlations supported all four hypotheses. Daily social media duration showed a small negative correlation with stress management self-efficacy (ρ = -0.17, p = 0.006). Passive use showed a moderate negative correlation (r = -0.41, p < 0.001). Active use showed a small positive correlation (r = 0.14, p = 0.024). Problematic use showed a moderate negative correlation (r = -0.38, p < 0.001).

Third, hierarchical multiple regression revealed that after controlling for demographic variables and shared variance among social media variables, passive use (β = -0.34, p < 0.001) and problematic use (β = -0.20, p = 0.003) emerged as significant unique negative predictors of stress management self-efficacy. Gender also remained significant, with female students reporting lower self-efficacy (β = -0.13, p = 0.019). The final model explained 25.0 percent of the variance in stress management self-efficacy.

Fourth, post-hoc comparisons revealed that students who used social media for more than six hours daily reported significantly lower stress management self-efficacy compared to those using for one to two hours or three to four hours.

Taken together, these findings indicate that passive and problematic social media use are consistently associated with lower stress management self-efficacy among university students, while active use shows only a weak positive relationship that does not hold when controlling for passive use.

5. Discussion

5.1 Summary of Findings

The primary purpose of this study was to investigate the relationship between social media use patterns (duration, passive use, active use, and problematic use) and stress management self-efficacy among university students. Data were collected from 263 university students through an online self-report questionnaire. The results provided support for all four research hypotheses. Specifically, daily social media duration showed a small negative correlation with stress management self-efficacy. Passive use demonstrated a moderate negative correlation, indicating that students who engaged in more passive scrolling and content consumption reported lower confidence in their ability to manage stress. Problematic use similarly showed a moderate negative correlation. In contrast, active use showed a small positive correlation with stress management self-efficacy, suggesting that students who posted, commented, and messaged more frequently reported slightly higher coping confidence. Hierarchical regression analysis revealed that passive use and problematic use remained significant unique negative predictors even after controlling for demographics and shared variance among social media variables, together explaining 25 percent of the variance in stress management self-efficacy.

5.2 Interpretation of Findings

5.2.1 The Role of Passive Social Media Use. The finding that passive social media use was the strongest negative predictor of stress management self-efficacy warrants careful interpretation. Passive use involves scrolling through feeds, watching others' content, and browsing profiles without direct interaction (Verduyn et al., 2015). When students engage in passive use, they are exposed to the curated, often idealized representations of their peers' lives. This exposure triggers upward social comparison, whereby individuals compare themselves unfavourably to others who appear more successful, happier, or more socially connected (Vogel et al., 2014).

From the perspective of Bandura's (1997) Social Cognitive Theory, self-efficacy beliefs are shaped by vicarious experiences and social persuasion. When students passively observe peers who seem to be managing their lives effortlessly, they may internalize the message that their own struggles with stress are abnormal or indicative of personal inadequacy. This vicarious experience undermines rather than strengthens self-efficacy because the observed models appear unrealistically competent. Furthermore, passive use displaces time that could be spent on mastery experiences—direct actions that build coping confidence through successful stress management. Instead of practicing relaxation techniques, seeking social support, or solving problems, students spend hours scrolling, which provides no opportunity to develop or rehearse coping skills.

The magnitude of the relationship (r = -0.41 in bivariate analysis, β = -0.34 in the final regression model) is notable. This effect size is larger than those reported in many studies examining social media and general well-being (Orben & Przybylski, 2019). One explanation is that stress management self-efficacy is a more specific and behaviourally relevant construct than global well-being. Passive use may directly undermine the belief that one can take action to cope with stress, whereas its effects on mood or life satisfaction may be more diffuse and subject to individual differences in resilience.

5.2.2 The Role of Problematic Social Media Use. Problematic social media use was also a significant negative predictor of stress management self-efficacy, both in bivariate analysis (r = -0.38) and in the final regression model (β = -0.20). This finding aligns with previous research linking addictive-like technology use to poorer mental health outcomes (Primack et al., 2017; Andreassen et al., 2016). However, the present study extends this literature by demonstrating a specific association with coping self-efficacy rather than merely with symptom measures.

Students who report problematic use patterns—feeling unable to cut back, using social media to forget problems, experiencing restlessness when prohibited—may be using social media as an avoidant coping strategy. Avoidant coping involves efforts to escape or ignore stressors rather than actively addressing them (Hoffner & Lee, 2015). While scrolling may provide temporary distraction, it does not resolve the underlying stressor. Over time, reliance on avoidant coping leads to a deterioration in perceived coping capability because the individual never receives feedback that active coping is effective. The problematic user's belief that they cannot manage stress without turning to social media becomes a self-fulfilling prophecy.

Importantly, problematic use and passive use were moderately correlated ($r = 0.44$) in the present study, suggesting that these two patterns often co-occur. Students who use social media excessively tend to engage in more passive consumption, and both patterns converge on the same outcome: lower confidence in one's ability to cope with stress.

5.2.3 The Limited Role of Active Use and Duration. The finding that active use showed only a small positive correlation ($r = 0.14$) that did not remain significant in the regression model is consistent with the differential effects hypothesis proposed by Verduyn et al. (2015). Active use posting, commenting, and direct messaging involves genuine social interaction that can foster perceived social support and a sense of belonging (Burke & Kraut, 2016). However, in the present study, the positive effect of active use was largely explained by its overlap with other variables. When passive use and problematic use were entered into the regression, active use ceased to be a significant predictor. This suggests that the benefits of active use may be overshadowed by the more powerful negative effects of passive and problematic use, or that students who engage in high levels of active use may also engage in some passive use that counteracts potential benefits.

Daily social media duration, while showing a small significant correlation with stress management self-efficacy ($\rho = -0.17$), was not a significant unique predictor in the regression model. This finding is methodologically important. It suggests that measuring only the quantity of time spent on social media is insufficient for understanding psychological outcomes. Two students who both spend five hours daily on social media could have very different experiences depending on how they use that time. One might spend four hours passively scrolling and one hour actively interacting, while another might do the reverse. The present findings indicate that the pattern of use matters more than the total duration. This supports the argument advanced by Valkenburg et al. (2022) that researchers must move beyond simplistic screen time measures.

5.2.4 Gender Differences. An unexpected but notable finding was that gender emerged as a significant predictor across all regression models, with female students reporting lower stress management self-efficacy than male students. This finding is consistent with previous research showing that female university students report higher perceived stress and lower coping self-efficacy compared to their male counterparts (Eisenberg et al., 2013; Saleh et al., 2017). Several explanations are possible. Female students may face additional stressors related to social expectations, body image concerns, and relational aggression that are amplified on social media platforms (Fardouly et al., 2015). Alternatively, female students may be more willing to acknowledge limitations in their coping abilities due to lower stigma around reporting psychological difficulties. Future research should examine whether the relationship between social media use and stress management self-efficacy differs by gender, as the present study did not find significant interaction effects (analyses not reported for brevity).

5.3 Comparison with Previous Literature

The findings of this study both align with and extend existing research. Consistent with previous studies, passive social media use was associated with poorer psychological outcomes (Verduyn et al., 2015; Thorisdottir et al., 2019). However, prior research has focused primarily on outcomes such as depressive symptoms, life satisfaction, and loneliness. The present study is among the first to specifically examine stress management self-efficacy as an outcome. This is theoretically important because self-efficacy is a modifiable psychological resource that mediates the relationship between stressors and mental health outcomes (Bandura, 1997). By demonstrating that passive and problematic use are associated with lower coping self-efficacy, this study identifies a mechanism through which social media may indirectly contribute to stress-related disorders.

The finding that problematic social media use was associated with lower stress management self-efficacy aligns with research on behavioural addictions. Andreassen et al. (2016) found that addictive social media use was associated with symptoms of anxiety and depression. The present study suggests that eroded coping confidence may be one pathway explaining this association. Individuals who believe they cannot cope effectively may be more vulnerable to developing psychiatric symptoms when faced with life stressors.

The weak and non-significant findings for active use are consistent with Burke and Kraut (2016), who found that receiving personalized communication from close ties predicted well-being, but that broadcasting to large audiences did not. The present study's active use scale included both one-to-one communication (direct messages) and one-to-many broadcasting (posting, commenting). Future studies might benefit from separating these distinct forms of active use, as they may have different effects on coping self-efficacy.

5.4 Theoretical Implications

The findings of this study have several theoretical implications. First, they support the application of Bandura's (1997) Social Cognitive Theory to digital environments. Self-efficacy beliefs are shaped by vicarious experiences, and social media provides an unprecedented volume of vicarious information about peers' lives. However, the nature of this information is systematically biased toward positive self-presentation. Students observing this curated content may draw inaccurate conclusions about their own coping abilities relative to others. Future theoretical work should consider how digital environments distort the four sources of self-efficacy (mastery experiences, vicarious experiences, verbal persuasion, and physiological states).

Second, the findings support the passive versus active use distinction as theoretically meaningful (Verduyn et al., 2015). This distinction should be incorporated into future theories of digital technology use and mental health. Simple dose-response models that assume more screen time is always harmful are theoretically impoverished. A more nuanced model would consider the psychological mechanisms (social comparison, social support, displacement) through which different usage patterns affect different outcomes.

Third, the results suggest that stress management self-efficacy should be included as an outcome variable in future studies of digital technology use. Most existing research has focused on affective outcomes (depression, anxiety) or global well-being. However, self-efficacy is a proximal predictor of behaviour and a target of many psychological interventions. Understanding how social media affects self-efficacy could inform intervention design.

5.5 Practical Implications

The findings of this study have several practical implications for university mental health services, student affairs professionals, and health educators.

First, interventions aimed at reducing problematic social media use should explicitly target coping self-efficacy. Simple messages to "spend less time on your phone" may be insufficient. Students need to understand why passive scrolling is problematic (social comparison, displacement of active coping) and how to replace it with more effective coping strategies. Psychoeducational workshops could teach students to recognize the difference between passive and active use, track their own patterns using screen time applications, and gradually replace passive scrolling with brief active coping exercises such as deep breathing, problem-solving, or reaching out to a supportive friend.

Second, university counselling centres should assess social media use patterns as part of routine intake for students presenting with stress-related concerns. A student who reports high passive use and low coping self-efficacy might benefit from a different intervention than a student with low social media use but high academic demands. Specifically, cognitive-behavioural interventions that address social comparison processes and build self-efficacy through behavioural experiments could be effective. For example, a student could be asked to reduce passive scrolling for one week and replace that time with a mastery experience (e.g., practicing a relaxation technique) while monitoring changes in coping confidence.

Third, digital literacy programs for incoming university students should address not only online safety and privacy but also the psychological effects of different usage patterns. Many students are unaware of the distinction between passive and active use or of the research linking passive scrolling to diminished well-being. Providing students with this knowledge empowers them to make intentional choices about their social media engagement. Simple strategies such as curating feeds to reduce exposure to upward social comparisons, setting time limits on specific apps, and designating phone-free periods for studying or sleeping could be taught in first-year orientation programs.

Fourth, the finding that female students reported lower stress management self-efficacy suggests that interventions may need to be tailored by gender. Female students might benefit from additional support in building coping confidence, perhaps through women-only support groups or mentoring programs that provide vicarious experiences of successful coping by female role models.

5.6 Limitations of the Study

Several limitations of this study must be acknowledged when interpreting the findings.

First, the cross-sectional design precludes any conclusions about causality. While the theoretical model assumes that social media use patterns affect stress management self-efficacy, reverse causation is equally plausible. Students with low coping self-efficacy may be more drawn to passive social media use as an escape from stressors they feel unable to manage. Longitudinal studies measuring both variables at multiple time points are needed to establish temporal precedence and direction of effects.

Second, all data were collected via self-report questionnaires, which are subject to several biases. Participants may have inaccurately recalled their social media use due to memory limitations or social desirability pressures to underreport use. Future studies should incorporate objective measures of social media use, such as application usage tracking software or browser extensions, to complement self-report data. Similarly, stress management self-efficacy was measured via self-report, which may be influenced by current mood state or personality characteristics such as neuroticism.

Third, the convenience and snowball sampling methods limit the generalizability of the findings. The sample was predominantly female (62.7 percent) and drawn from students who had access to online survey links distributed through university groups. Students who are heavier social media users may have been more likely to see and respond to the survey invitation, potentially biasing the sample toward higher levels of use. The findings may not generalize to university students in different cultural contexts, to non-university young adults, or to older populations.

Fourth, the study did not measure several potentially important confounding variables. Personality traits such as neuroticism, conscientiousness, and extraversion are known to be associated with both social media use patterns and coping self-efficacy (Kuss & Griffiths, 2017). Without measuring these traits, it is possible that the observed relationships are partially or fully explained by underlying personality differences. Similarly, the study did not assess mental health diagnoses, life stressors, or social support outside of social media.

Fifth, the study focused exclusively on university students, a population that faces unique developmental stressors and has near-universal social media access. The findings may not generalize to other populations, such as working adults, adolescents, or older adults, whose social media use patterns and stress management resources may differ substantially.

Sixth, the study did not differentiate between specific social media platforms. Instagram, TikTok, Snapchat, and X (formerly Twitter) have different affordances, user demographics, and typical use patterns. Passive scrolling on image-focused platforms like Instagram may trigger different psychological processes (body comparison, envy) than passive scrolling on text-focused platforms like X (social comparison about achievements or opinions). Future research should examine platform-specific effects.

5.7 Recommendations for Future Research

Based on the findings and limitations of this study, several directions for future research are recommended.

First, longitudinal studies are urgently needed to establish the direction of causality between social media use patterns and stress management self-efficacy. Researchers could recruit first-year university students and measure both variables at the beginning of the academic year, at mid-year, and at the end of the year. Cross-lagged panel analyses would reveal whether early passive use predicts later declines in self-efficacy, whether low self-efficacy predicts increased passive use, or both. Such studies would provide stronger evidence for intervention targets.

Second, experimental studies could provide causal evidence. Researchers could randomly assign participants to different social media use conditions for a period of one to two weeks. For example, one group could be instructed to replace passive scrolling with active interaction, another group to reduce total use by 50 percent, and a control group to use social media as usual. Changes in stress management self-efficacy from pre- to post-intervention could be compared across conditions. Such experiments would provide actionable guidance for interventions.

Third, future research should incorporate objective measures of social media use. Smartphone applications such as Screen Time (iOS) or Digital Wellbeing (Android) can track total usage time and time per application. Some research platforms allow for passive sensing of social media behaviour, capturing not only duration but also patterns of switching between apps and times of day when use occurs. Combining objective data with self-report measures would reduce recall bias and provide a more accurate picture of actual behaviour.

Fourth, qualitative research could illuminate the lived experience of students who report high passive use and low stress management self-efficacy. Semi-structured interviews could explore questions such as: What do students think and feel while scrolling passively? What prevents them from shifting to more active coping strategies? How do they perceive their own coping abilities relative to peers they see online? Such qualitative insights could inform the development of more targeted and acceptable interventions.

Fifth, future studies should examine potential moderators of the relationship between social media use and stress management self-efficacy. For example, social support may buffer the negative effects of passive use. Students with strong offline social networks may be less affected by online social comparison because they have alternative sources of validation and support. Similarly, dispositional mindfulness or self-compassion might protect against the self-efficacy-diminishing effects of passive scrolling. Identifying moderators would help target interventions to those most at risk.

Sixth, cross-cultural research is needed to determine whether the findings generalize across different cultural contexts. Social media use patterns, norms around self-presentation, and cultural values regarding stress and coping vary substantially across countries. A study comparing university students in collectivist versus individualist cultures, or in countries with high versus low smartphone penetration, could reveal important contextual factors that shape the relationship between social media use and coping self-efficacy.

Seventh, intervention research should test whether reducing passive social media use or promoting active use leads to measurable improvements in stress management self-efficacy. A randomized controlled trial could compare a brief educational intervention (teaching students about passive versus active use) to a behavioural activation intervention (helping students replace passive scrolling with active coping behaviours) to a waitlist control. Outcomes would include stress management self-efficacy, perceived stress, and mental health symptoms measured at baseline, post-intervention, and three-month follow-up.

5.8 Summary of Contributions

This study investigated the relationship between social media use patterns and stress management self-efficacy among 263 university students. The findings make several important contributions to the literature. First, the study demonstrated that not all social media use is equal. Passive use, characterized by scrolling and consuming content without interacting, was consistently associated with lower stress management self-efficacy, whereas active use showed a weak positive relationship that did not hold in multivariate analyses. Second, problematic or addictive-like social media use was also associated with lower coping confidence. Third, daily duration alone was a weak predictor, underscoring the importance of measuring how students use social media rather than simply how much. Fourth, the final regression model explained 25 percent of the variance in stress management self-efficacy, with passive use and problematic use emerging as the strongest unique predictors.

5.9 Answering the Research Questions

The study was guided by four hypotheses. Hypothesis One, which predicted that greater daily time spent on social media would be negatively associated with stress management self-efficacy, was supported, though the effect was small. Hypothesis Two, predicting a negative association for passive use, was strongly supported with a moderate-to-large effect size. Hypothesis Three, predicting no significant or a weak positive association for active use, was supported as a small positive correlation was observed that did not remain significant in regression. Hypothesis Four, predicting a negative association for problematic use, was strongly supported with a moderate effect size.

Taken together, these findings indicate that university students who engage in high levels of passive scrolling and who report problematic patterns of social media use are at risk for lower confidence in their ability to manage stress. This is concerning given that stress management self-efficacy is a known protective factor against the development of anxiety, depression, and burnout (Schönfeld et al., 2016; Steinhardt & Dolbier, 2008).

5.10 Final Remarks

University students navigate a developmental period characterized by multiple stressors while simultaneously being the heaviest users of social media. The present study suggests that the way students engage with social media matters for their psychological resources. Passive consumption of idealized content may erode the very confidence students need to cope effectively with academic and personal challenges. However, this is not a deterministic relationship. Self-efficacy beliefs are malleable, and social media use patterns are behavioural choices that can be modified.

Universities have a role to play in promoting digital literacy that goes beyond privacy and safety to include psychological well-being. Teaching students to recognize the effects of passive scrolling, to curate their feeds to reduce harmful social comparisons, and to replace passive use with active coping strategies could help preserve and strengthen stress management self-efficacy. At the same time, students should be empowered to make their own choices, with the understanding that moderate, intentional, and active social media use may have different effects than the passive, compulsive scrolling that has become normative.

Future research should continue to refine our understanding of these relationships through longitudinal, experimental, and qualitative designs. In an era where digital technology is ubiquitous, understanding how it shapes the psychological resources of young people is not merely an academic question but a public health priority. The present study takes an initial step in this direction by focusing on stress management self-efficacy, a construct at the intersection of digital behaviour and mental health resilience.

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