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The Mediating Role of Smart Learning in the Relationship Between Social Media and Mental Well-Being Among University Students

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Abstract

The purpose of this study was to investigate the relationship between social media (SM) and mental well-being (MWB) and then establish the mediating role of smart learning between social media and metal well-being among university students in Kenya. The study used convenience sampling technique, data was collected from 456 respondents using a self-administered questionnaire and then analyzed through partial least squares-structural equation model (PLS-SEM). The findings of this study establishes that social media has a positive and significant influence on mental well-being ($\beta = 0.25$, $t = 3.597$, $p < 0.000$;), smart learning ($\beta = 0.574$, $t = 8.897$, $p < 0.000$). Simultaneously, smart learning also had a positive and significant influence on mental well-being ($\beta = 0.252$, $t = 3.867$, $p < 0.000$) and partially mediates between the social media and mental well-being ($\beta = 0.25$, $t = 3.597$, $p < 0.000$) among university students. The study recommends the university administrators to prioritize investment in social media technology platforms with the view of enhancing students' mental well-being and streamline smart learning environment in the higher education institutions.

Keywords: *Social media, smart learning, mental well-being, university students.*

Introduction

In recent years, the penetration and ubiquity of social media has become an integral part of our daily lives and significantly transformed how we communicate, interact and access information. This transformation holds particular salience for the young adults, for whom the integration of social media has become nothing of indispensable in both their educational and daily experiences (Shahzad, *et al*., 2024). In the field of education, the use of social media has become a top priority due to abundance of cutting-edge learning opportunities and experiences for students in accessing course content, data collection, forming study groups and collaboration purposes (O'Brien, 2012; Ansari & Khan, 2020). In recent times, universities have witnessed an immense popularity and surge in the usage of social media tools such as YouTube, Meta (formerly Facebook), Instagram, WhatsApp, X (formerly) Twitter, TikTok, etc., by both students and faculty members (Chowdhury, 2024).

This usage trend has been massively adopted particularly by younger generation to promote teaching and learning both inside and outside the classroom. Empirical studies have shown that the use of social media technologies has several benefits (Alwagait *et al*., 2015). These benefits include; enhanced communication between students and instructors, increased opportunities for networking or collaborations among students both near and far, rapid sharing of study materials, access to course materials, provision of alternative platform to the official learning management systems and exposure of students to technologies and skills that may improve their employment success (Legaree, 2015). Despite this essential nature of these social media technologies and benefits, their synergistic impact on mental well-being among students remains underexplored and thus necessitates research attention (Hosen *et al.,* 2021).

Statement of the Problem

While extant literature and previous studies predominantly addresses the technical and pedagogical dimensions of social media on education (Chowdhury, 2024; Haleem, et al., 2022; Cheng, et al., 2022; Bhandarkar, et al., 2021), a clear research lacuna exists on the health welfare of university students' interaction with the various social media platforms in modern digitized education era. Hence, this research aims to bridge this critical gap by exploring the significant relationships among social media, mental well-being and the mediating role of smart learning among university students in the Kenyan educational context.

Research hypotheses

The aim of this study was to test these research hypotheses as shown in Figure 1:

i. Social media (SM) significantly affects the mental well-being (MWB)of university students?

ii. Social media significantly affects the smart learning (SL) environment in the university?

iii. Smart learning significantly influences the mental well-being of university students?

iv. Smart learning mediates between the relationship of social media and mental well-being among university students?

Literature Review

Theoretical Review

Social Learning Theory

Over the past decade, the world has witnessed a tremendous penetration and ubiquity of social media technologies (Kahveci, 2015). This has significantly altered and transformed our daily lives, including how we interact, communicate and access information. This transformation witnesses a correlative observation regarding social media and its effects on younger generation times, resources and self-expression (Shahzad *et al.*, 2024). In the context of education, Social Learning Theory (SLT) has become widely employed on social media to stimulate attention, memory and motivation, which enhances the acquisition of knowledge (Daniels & Billingsley, 2014).

Bandura's seminal theory in 1969 laid the groundwork for understanding how diverse engagements with social networks and collaborative technologies such as social media platforms significantly influence learning experiences and outcomes (Jia *et al.*, 2023). Furthermore, Bandura's social learning theory holds that, learning takes place in a social setting where people, environments and behaviors are always changing. Therefore, educators have a unique opportunity to apply the concepts of Social Learning Theory toward enhanced student engagement and learning in a social media context. In recent times, educators in higher education sectors leverages on using social platforms such as YouTube, Instagram, WhatsApp among others to support social learning. In addition, a lot of learning management systems have social media integration or even use of third-party social media tools to enhance the learning experiences (Deaton, 2015).

The engagement with social media technologies and applications integrates seamlessly with social learning theory' scope. These tools serves as an extension of social networks and as customized pedagogical agents that can deeply impact learning outcomes and mental well-being (Shahzad, *et al.,* 2024). Moreover, smart learning as conceptualized through diverse measures such as group goals alignment, affinity for novel technologies and social media applications connect well with the core tenets of social learning theory (Ali, *et al.,* 2018). In smart learning, the affinity for exploring a broad range of subjects reflects the social learning theory's emphasis on external circumstances and peer influences in shaping learning outcomes (Kaliisa, *et al.,* 2022). One is not just a passive recipient of information but am active seeker of diverse knowledge. This aligns with Albert Bandura's assertion that individuals in social setting actively initiate and coordinate their learning processes (Grover, *et al.,* 2022). Therefore, the nexus of social media technologies and social learning theory offers a robust analytical lens through which researchers can assess the impact of social media platforms on mental welfare, mediated by smart learning.

Empirical Review

Social Media and Mental Well-Being

Mental well-being is a state reached when every individual realizes their own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to their community (WHO, 2025). In the recent times, increased online connectivity and access to new emerging technologies such as smartphones have paved the way for social media to become a prominent method for social interaction, access to information and content sharing (Cuello-Garcia, *et al.,* 2020). As of July 2024, nearly 5.17 Billion people are at least on social media site and the average time spent on social media is 140 minutes per day (Statista, 2024).

Recent research underscores that social media usage has been found to have an impact on students' mental health in both positive and negative ways (Whelan, *et al.,* 2022; Granic, *et al.,* 2020). However, there is no consensus on whether or not that impact is positive or negative (Bowman, 2013; Kim & Kim, 2017). Some studies have highlighted the negative effects of the social media on subjective psychological well-being (Nadelson, 2017) and self-esteem (Zhao, 2021; Hawi & Samaha, 2017). For instance, Tandoc and Collegues (2015) found that university students with larger social networks were more likely to experience envy and depression. Another study by Hawi and Samaha (2017) found that there was no direct relationship between social media addiction and satisfaction with life.

In contrast, other researchers have argued that social media usage have positive effects on university students well-being (Shahzad, *et al.,* 2024; Hollis *et al.*, 2020; Pittman & Reich, 2015). Feeling of loneliness may decrease with the use of social media platforms (such as Instagram and snap-chat), potentially due to increased sense of intimacy associated with images and text (Pittman & Reich, 2015). Taken collectively, these conflicting views and outcomes call for a nuanced evaluation of the intricate relationship between social media and mental well-being particularly in the universities in the Kenyan context.

Social Media and Smart Learning

Despite the popularity and pervasive role of social media in our everyday lives, we have little academic understanding of how "social" social media actually is. Social media is defined as a group of internet-based application that build on the ideological and technological foundations of web 2.0, and allow the creation and exchange of user generated content (Boyd & Ellison, 2007). On the other hand, smart learning is a technology-supported learning that adapts and provides appropriate support in the right place and time based on individual needs, which could be determined by analyzing their behaviour and results (Zhu *et al.,* 2016). Integration of social media and smart learning aims to provide students with self-learning, self-motivation and personalized opportunities, allowing them to attend classes at their speed and access personalized learning content tailored to their specific needs. Recent study has acknowledged the importance of smart learning as a mediator between artificial intelligence and mental well-being and social media and mental well-being (Shahzad *et al.,* 2024).

Smart Learning and Mental Well-Being

The term "Smart Learning" is now commonly used to describe online education. It demonstrates how learners can use knowledge and skills more easily, successfully, and simply due to convergence of modern digital technologies (Al-Nabhani & Pulparambil, 2024). The overarching goal is to create a smart learning environment (SLE) that is more relevant, dynamic and efficient, allowing students to learn more effectively and successfully (Allal-Ch´erif *et al.,* 2021). This form of pedagogical evolution manifests through customized, interactive learning experience fortified by the analytical capabilities of social utility of social media platforms (Muro *et al.,* 2018). According to Samaha *et al.,* (2016), smart learning environment empower students with unparalleled access to educational materials, collaborative platforms and personalized feed-back loops, thereby enriching self-directed learning and provide more engaging education experiences.

In the recent times, several educational institutions are leveraging smart learning to bolster student engagement, foster collaborative learning ecosystem and promote mental well-being (Boer *et al.,* 2020). Furthermore, several universities are particularly seizing technological dividend of smart learning to enhance engagement and inclusive education ecosystem that support that support both student academic performance and wellness (Barth Vedøy *et al.*, 2020). A seminal study paper by (Embarak, 2022) found that, smart learning interventions exert a positive impact on students mental well-being. Furthermore, a recent study has acknowledged the importance of smart learning as a mediator. For instance, Shahzad, *et al.,* (2024) examined that overall, smart learning partially mediates between artificial intelligence and mental well-being and social media and mental well-being.

Conceptual Framework

A conceptual framework is typically a visual representation (although it can also be written out) of the expected relationships and connections between various constructs or variables. This study variables mapping is illustrated in Figure 1.

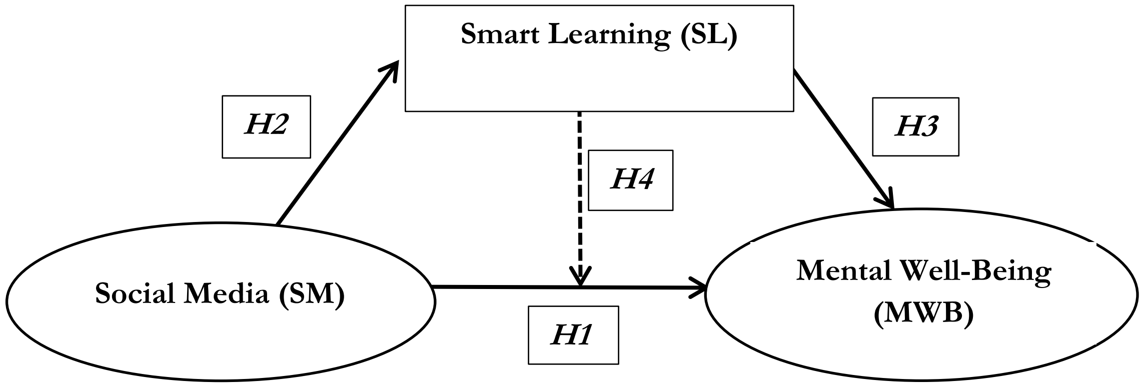

Figure 1: *Conceptual Model*

Research Methodology

Measurement

The study used face-to-face self-administered questionnaire survey with a well-structured closed-ended questions formulated to achieve the intended study's objectives. There were three main constructs for the study. The questionnaire was dissected into two sections, i.e. sections A and B. Section A contained information regarding demographic characteristics. Similarly, section B consisted of items related to the three main constructs of the present study-social media, smart learning and mental-well-being, which have been taken from different previous studies. All the constructs were tested using five-point Likert scale where the students were instructed to indicate their level of agreement with each statement ranging from 1=strongly disagree to 5=strongly agree.

Sampling and Data Collection

The study's total sample size was 456 respondents. The convenience sampling technique was used to collect the data. The benefits of this technique include the ability to precisely target respondents and therefore reduce the difficulty of locating them, which in turn significantly reduces the cost of undertaking the survey (Sekaran & Bourgie, 2016). The respondents were selected from several different classes within the university which was done randomly. After classes were identified, the questionnaires were distributed during class time after approval from the instructors in charge of the classes. The students were informed about the purpose of the study, its significance, and assured of preservation of their anonymity, confidentiality of the information supplied and total adherence to all ethical guidelines. They were also informed that the participation in the survey was voluntary. Once agreed to participate, they were given between 5 and 10 minutes to fill the questionnaire. Thus, 500 questionnaires were distributed, 475 were obtained and 456 were valid for analysis after screening.

As a result, the survey received 91.2% of the responses. The internal reliability was validated using Cronbach's alpha. For the analysis of the data, descriptive statistics were performed using SSPS, and structural equation modelling (SEM) was done using AMOS v26.

In addition, structural models' fit was assessed using the overall model fit indices, which consist of chi-square ($\chi 2$)/degree of freedom ratio (CMIN/DF), root mean square error of approximation (RMSEA), goodness of fit index (GFI), comparative fit index (CFI), normed fit index (NFI) and Tucker–Lewis index (TLI).

Results and Findings

Respondent profile

The data was gathered through a survey from the students of different schools. The sample consisted of 456 respondents, of who, 192 (41.92%) were male and 266 (68.08%) were female. Concerning the education levels, 306 (66.81%) were in bachelor's degrees, 143 (31.22%) in master's degrees and 9 (1.97%) in doctoral degrees. Furthermore, in terms of ages, 154 (33.77%) fell within 17 to 21 years age brackets, 192 (42.11%) in the 22 to 27 years categories, 65 (14.25%) at 28 to 35 years range and 45 (9.87%) were above 35 years. Regarding daily internet usage, 120 (26.28%) reported using the internet for 1 to 4 hours, 219 (47.92%)for 4 to 8 hours and 118 (25.82%) for more than 8 hours. Lastly, 9 (1.98%) were undertaking doctor of business administration program (DBA), 48 (10.48%) Master of business administration (MBA), 39 (8.52%) Master of science in management of information system (MSc-MIS), 52 (11.25%) Master of science in management of organizations (MSc-MOD), 56 (12.23%) international relations (IR), 59 (12.88%) technology, 51 (11.14%) psychology, 41 (8.95%) international business administration (IBA), 76 (16.59%) account and finance and 37 (5.90%) were undertaking other undergraduate degrees programs.

The respondents' data is summarized by calculating the mean, standard deviation, skewness and kurtosis of variables like social media (SM), smart learning (SL) and mental well-being (MWB). Table 1 shows the descriptive statistics of the study variables. Smart learning has the highest mean value of 3.474 and social media has a low mean value of 3.182. On the other hand, social media has less variation which indicates a standard deviation of 0.637, and mental-well-being has more variations which is indicated by a standard deviation of 0.726.

Table 1

Descriptive Statistics

Construct	Mean	SD	VIF	Skewness	Kurtosis
Mental Well-Being (MWB)	3.290	0.726		-0.458	0.459
Smart Learning (SL)	3.474	0.690	1.708	-1.375	2.353
Social Media (SM)	3.182	0.637	1.708	-0.654	0.928

Sample Adequacy Test

For sample adequacy test, the Kaiser-Meyer-Olkin (KMO) test is conducted. According to Kaiser and Rice (1974), if the KMO value is more than 0.6, the data is sufficient to conduct statistical analysis like EFA. For this present study, the value is 0.876 indicating the sample data is adequate to conduct EFA. To check the non-zero correlation among the study variables items, Barlett's test of sphericity is considered appropriate and a small significance level is a good indication of a non-zero correlation among the items, and the collected data is sufficient to proceed with EFA (Tobias & Carlson, 1969). This study test results show that the *p*-value is less than 0.000, indicating that the proposed items have a non-zero correlation and that data is suitable to conduct EFA as shown in Table 2.

Table 2

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.876
Bartlett's Test of Sphericity	Approx. Chi-Square	3519.868
	df	136
	Sig.	0.000

Measurement Model

The measurement model serves as a rigorous framework to substantiate the dependability of the constructs and to authenticate their validity). Utilizing PLS-SEM, this present study focused on four key parameters: factor loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) as shown in Table 3, alongside Fornell-Larcker criteria and model fit indices. The first step in evaluating the measurement model involved analyzing the factor loadings of all three reflective constructs. To identify the predominant measurement items in the designed survey instrument, EFA was conducted using varimax rotation under the principal component analysis method. For the present study, 17 items were extracted and based on the relevance of the items, factors were grouped into three and named as social media (six items), smart learning (five items) and mental-well-being (six items). Table 4 displays the item factor loadings on the three constructs. According to Hair *et al*., (2014), all 17 items has considerable factor loadings above 0.5 which is an acceptable threshold recommended in multivariate analysis literature. This outcome shows a strong correlation between them and the respective factors.

The internal consistency of the designed instrument was assessed through Cronbach's alpha value and composite reliability to confirm the reliability of the items. As shown by the data (Table 4), the Cronbach's values were 0.903 for social media, 0.871 for smart learning and 0. 856 for mental-well-being and composite reliability scores of 0.812, 0.872 and 0.859 respectively. Each construct had a satisfactory level of internal consistency, with values exceeding the threshold of 0.60 as recommended by Hair *et al.,* (2017). This exemplify a robust internal consistency.

The convergent validity of the measurement model was demonstrated by standardized loading of each construct as well as the average variance extracted (AVE). The AVE values for social media, smart learning and mental-well-being were 0.502, 0.583 and 0.505 respectively. All three constructs exceeded the minimum threshold of 0.5 and therefore confirming convergent validity (Hair *et al.,* 2018). Furthermore, CR of more than 0.6 for each construct would also be considered as good estimate of convergent validity (Bagozzi & Yi, 1988) as shown on Table 3.

Table 3

Measurement Model Results

Constructs	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Social Media		**0.903**	**0.812**	**0.502**
SM1	0.659			
SM2	0.561			
SM3	0.695			
SM4	0.802			
SM5	0.780			
SM6	0.699			
Smart Learning		**0.871**	**0.872**	**0.583**
SL1	0.858			
SL2	0.617			
SL3	0.743			
SL4	0.919			
SL5	0.895			
Mental Well-Being		**0.856**	**0.859**	**0.505**
MWB1	0.690			
MWB2	0.794			
MWB3	0.757			
MWB4	0.840			
MWB5	0.737			
MWB6	0.738			

The assessment of discriminant validity was undertaken using Fornell-Larcker criterion, which ensures that each variable is distinctly separate from all others within the same constructs. The square roots of the AVE of the constructs were, social media (0.709), smart learning (0.784) and mental-well-being (0.711), which were greater than the correlation values among the competing variables. As shown in Table 5, the discriminant validity of each variable exceeded 0.7, thereby fulfilling the Fornell-Larcker criterion as suggested by Hair *et al.,* (2017).

Table 4

Discriminant Validity-Fornell-Larcker Criterion

Construct	MWB	SL	SM
Mental Well Being	**0.711**		
Smart Learning	0.395***	**0.764**	
Social Media	0.394***	0.574***	**0.709**

To verify the proposed measurement model, extracted factors from EFA were tested using CFA (maximum likelihood method) with SPSS-AMOS software. The result of CFA indicates three factors along with the 16 items in the proposed model which is represented in Figure 2.

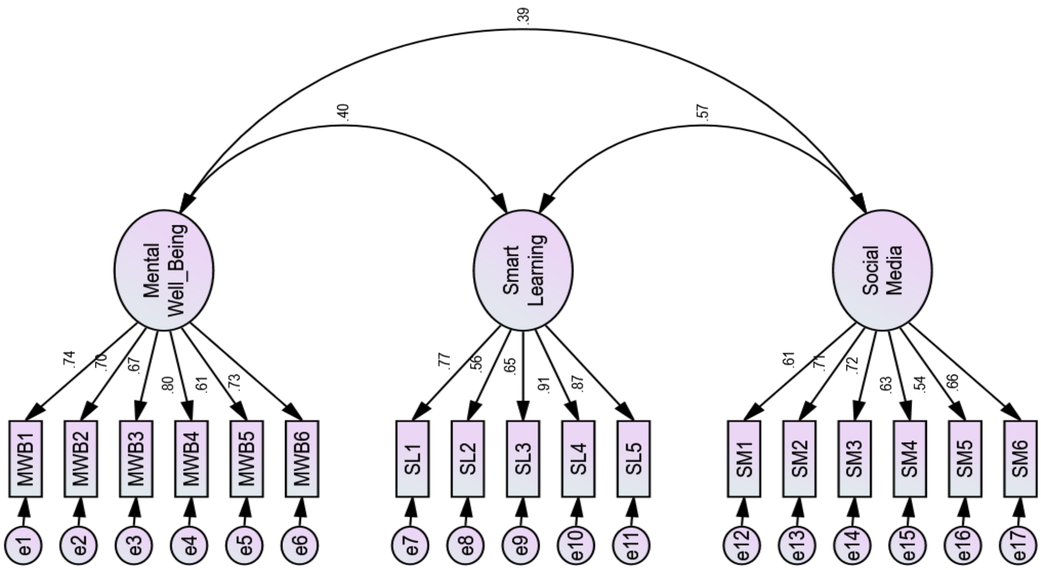

Figure 2: Measurement Model

The test statistics were as follows; CMIN/DF=2.905, GFI= 0.908, CFI=0.922, NFI= 0.913 and TLI=0.915 as shown in Table 6. All these measured indices fulfilled the recommended thresholds for fitness indices (CMIN/DF < 5, GFI, CFI, NFI, TLI >0.9). RMSEA = 0.071, which is less than 0.08 indicating the proposed three factor model is capable of measuring the intended objective as recommended by Hair *et al.,* (2019).

Table 5

Summary Statistics for Measurement Model Fitness Indices

Model Indices	CMIN/DF	RMSEA	GFI	CFI	NFI	TLI
Model score	2.905	0.071	0.908	0.922	0.913	0.915

Structural Equation Modeling and Hypotheses Testing

SEM is a statistical approach used to investigate the relationship between variables and verify the proposed model (Hair *et al.,* 2006). It helps investigating the direct and indirect influences of constructs on one another, as well as evaluating the model's overall structure. To analyze this present study hypotheses, partial least square structural equation modelling techniques, with the aid of SmartPLS was used as shown in Figure 3, Table 6 and Table 7.

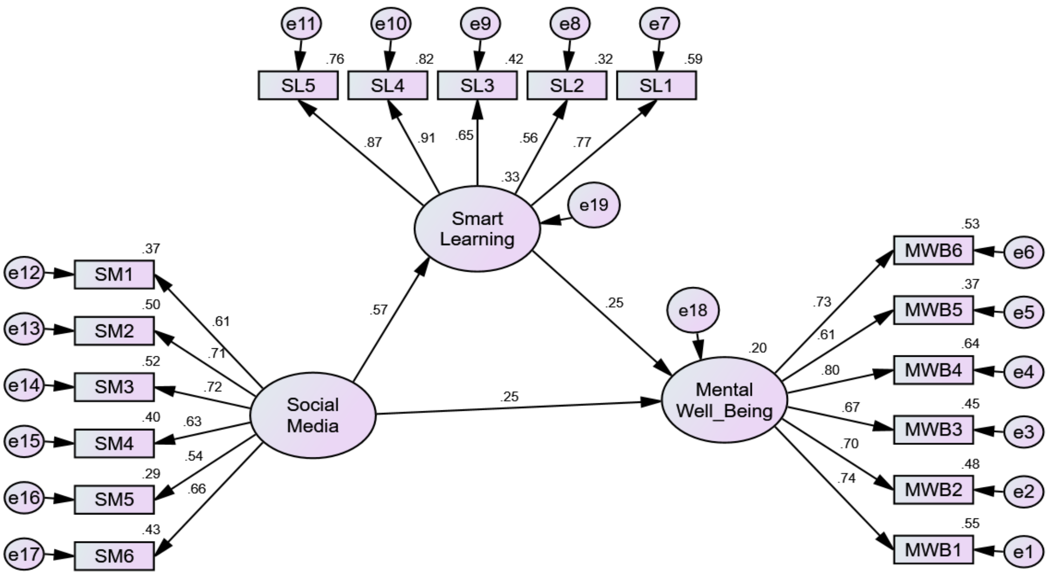

Figure 3. *Structural model*

The hypothesized overall structural relationships is given in Figure 3. The results revealed that there is significant direct effect of social media (SM) on mental well-being (MWB)($\beta = 0.25$, $t = 3.597$, $p < 0.000$), supporting hypothesis *H1* as shown in Table 6.

Table 6

Direct Path Analysis for Hypothesis one

Hypothesis	*β*- value	*T*- value	*P*- value	Decision
H1 SM > MWB	0.393	6.423	0.000	Support

Similarly, there was significant effect of social media (SM) on smart learning (SL)($\beta = 0.574$, $t = 8.897$, $p < 0.000$) and smart learning (SL) on mental-well-being (MWB) ($\beta = 0.252$, $t = 3.867$, $p < 0.000$), supporting *H2* and *H3* as shown in Table 7.

Table 7

Overall Path Analysis

Hypothesis	*β*- value	*T*- value	*P*- value	Decision
H2 SM > SL	0.574	8.897	0.000	Support
H3 SL > MWB	0.252	3.867	0.000	Support
H4 SM > SL > MWB	***0.25***	***3.597***	***0.000***	***Partial Médiation***

Mediation Analysis

The study explored the mediation role of smart learning in the relationship between social media and mental-well-being. The results demonstrated that, the direct correlation effect between social media and mental-well-being decreased from ($\beta = 0.393$, $t = 6.423$, $p < 0.000$) as shown in Table 7 to ($\beta = 0.25$, $t = 3.597$, $p < 0.000$) indirect effect with insertion of smart learning as a mediator as shown in Table 8-overall path analysis. The results indicate that smart learning mediates the relationship between social media and mental-well-being support *H4* as shown in Table 7.

Discussion of Results

Social media deep integration into the fabric of modern life has fundamentally shifted the paradigms in diverse sectors ranging from education to interpersonal communications (Shahzad, *et al.,* 2024). The advancements have brought invaluable benefits but also raised critical questions about their impacts on mental well-being (Lee, 2023). Recognizing the magnitude of these concerns, the primary aim of this current study was to rigorously investigate students' perceptions of the nexus between social media and mental well-being within the context of smart learning as a mediator. The findings of the research reveal that social media positively and significantly affects the mental well-being of students, hence supporting *H1.* This conforms with the prior results of Lee, (2021), Young *et al.,* (2020) and Shahzad *et al.,* (2024), which revealed that social media enhances mental well-being. Therefore, university administrators and policymakers need to pay more attention to social media technologies to enhance emotional support, mental resilience and social connectedness, hence mitigating feelings of isolation and loneliness (Young *et al.*, 2020).

Moreover, the study also demonstrates that smart learning has a significant influence on mental well-being hence support *H2.* This is with previous study, which demonstrated that smart learning has a significant and positive impact of mental well-being (Shahzad *et al.,* 2024). Therefore, policymakers need to pay more attention to technology-enhanced education by investing on the emerging digital technologies for university community support and making vital education information becoming more accessible, thereby democratizing mental health welfare services. Finally, the results of mediation effect indicated that smart learning partially mediates between social media and mental well-being of the university students. Accordingly, H4 is confirmed, and the results are congruent with the findings of Shahzad *et al*. (2024). In summary, this study offers a compelling and robust empirical foundation for administrators and policymakers to formulate policies on the nexus of social media technologies and platforms and mental well-being in the era of digitalization.

Conclusion

Social media and smart learning environments are revolutionizing education sector by personalizing learning, catering to individual student needs, and enhancing engagement through interactive elements, potentially improving learning outcomes. Responsible development, equitable access to technology by all, proper technology-enhanced education support, and robust data privacy and security protocols are crucial for unlocking the full potential of social media. Despite social media and smart learning environment offering personalized, engaging, and effective learning experiences for university students, responsible implementation and proper addresses of potential challenges create a brighter future for university students and enhance their mental well-being. Social media is set to revolutionize education by enhancing personalized instruction, tracking student progress, providing valuable insights into student performance, and enhancing resource efficiency. It will also help universities become smarter, leading to more efficient decision-making and a more equitable learning environment. Despite skepticism, the promise of social media in education sector and students mental well-being is becoming increasingly attractive, as it can solve universal issues and increase engagement with learning activities.

Theoretical and Managerial Implications

Theoretical Implications

Due to proliferation of web 2.0 (Meta-formerly Facebook, Instagram, YouTube, X-formerly Twitter, WhatsApp, TikTok etc.) usage after COVID-19 pandemic and widespread internet access across the globe, social media has risen to prominence both as an educational and communication tool. This present study attempts to test empirically the relationship between social media and mental-well-being among university students and employing smart learning as a mediator. The study not only provides a theoretical framework for understanding social media behaviour among university students, but it also develops a conceptual model for investigating the influence of social media on mental-well-being among students. Additionally, the current study reveals that social media has a substantial impact on mental-well-being. The findings have already been confirmed by previous studies before this current study such as Lee, (2021), Young *et al.*, (2020) and Shahzad *et al.,* (2024), but not among university students in emerging market like Kenya. The finding that social media has a positive impact on mental-well-being is extremely imperative for high education stakeholders. However, this present study contributes to the existing literature in multiple ways.

First, this study attempts to enrich the published literature with social media and mental-well-being of students by considering smart learning as a mediator in higher education. It is possible to claim that no single study has demonstrated how social media influences mental-well-being with smart learning as a mediator for university students in Kenya. As a matter of facts, the current study bridges the gap by providing a robust theoretical framework for future researchers. Second, this present research provides an in-depth conceptual model by examining the notions of social media, smart learning and mental-well-being through the perspectives of Kenyans university students that would help future scholars and researchers gain a better grip of the subject. Third, the findings confirm the significance of smart learning environment in its role as a mediating construct to bolster and enhance education experiences among university students. Simultaneously, this study will also help higher education administrators and faculties consider leveraging and investing more on social media as a transformative educational tool.

Managerial Implications

Following the theoretical implications and the findings of this current study, the study also has some managerial implications for university administrators and faculties particularly in the Kenyan context. The results suggest that smart learning has a substantial role in social media and mental well-being. In this sense, with the proliferation of internet usage, funding allocations for research and development of smart learning technologies as well as the formulation of best practices guidelines can be particularly useful. Turning our attention to students, for them to navigate the digital age, it is also imperative for the university administrators to foster a supportive, digitally responsible environment that enhances the community well-being. Furthermore, the outcomes of this research point the needs for university policymakers to construct policies that strikes a balance between technological innovation and university community health welfare. Additionally, it challenges the administrators to offer professional development opportunities for faculties and the entire student body to stay abreast the emerging digital trends and implication of the same to students mental well-being. Finally, the administrators need to consider potential negative externalities such as online harassment, cyberbullying, privacy breeches and misinformation are well addressed within the institutions (Shahzad *et al.,* 2024).

References

Allal-Ch´erif, O., Yela-Aranega, A., & Castano Sanchez, R. (2021). Intelligent recruitment: how to identify, select, and retain talents from around the world using artificial intelligence, *Technol. Forecast. Soc. Change 169,* https://doi.org/10.1016/j.techfore.2021.120822.

Al-Nabhani, B.K.S., & Pulparambil, S. (2024). A comprehensive review on artificial intelligence and learning theories. *International Journal of Research and Scientific Innovation,* 2321-2705 | DOI: 10.51244/IJRSI | Special Issue |Volume XI Issue XIV.

Alwagait, E., Shahzad, B., & Alim, S. (2015). Impact of social media usage on students' academic performance in Saudi Arabia., *Computers in Human Behavior, 51*, 1092-1097.

Ansari, J.A.N., & Khan, N.A. (2020). Exploring the role of social media in collaborative learning the new domain of learning, *Smart Learning Environments, 7* (1), 1-16.

Bagozzi, R. P., & Yi, Y.-J. (1988). On the Evaluation of Structural Equation Models. Journal of the *Academy of Marketing Science*, *16*, 74-94. https://doi.org/10.1007/BF02723327.

Barth Vedøy, I., Anderssen, S.A., Tjomsland, H.E., Skulberg, K.R., & Thurston, M. (2020). Physical activity, mental health and academic achievement: a cross-sectional study of Norwegian adolescents, *Ment. Health Phys. Act.* 100322, https://doi.org/10.1016/j.mhpa.2020.100322.

Bhandarkar, A.M., Pandey, A.K., Nayak, R., Pujary, K., & Kumar, A. (2021). Impact of social media on the academic performance of undergraduate medical students, *Medical Journal Armed Forces India*, 77, S37-S41.

Boer, M., Stevens, G.W.J.M., Finkenauer, C., de Looze, M.E., & van den, R.J.J.M. (2021). Eijnden, Social media use intensity, social media use problems, and mental health among adolescents: investigating directionality and mediating processes, *Comput. Human Behav.* 116106645, https://doi.org/10.1016/j.chb.2020.106645.

Bowman, N.A. (2013). How much diversity is enough? The curvilinear relationship between college diversity interactions and first-year student outcomes. *Res High Educ, 54*:874–94. https://doi.org/10.1007/s11162-013-9300-0.

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

Cheng, L., Fang, G., Zhang, X., Lv, Y., & Liu, L. (2022). Impact of social media use on critical thinking ability of university students", *Library Hi Tech,* Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/LHT-11-2021-0393.

Chowdhury, E.K. (2024). Examining the benefits and drawbacks of social media usage on academic performance: A study among university students in Bangladesh, *Journal of research in innovative teaching & learning,* 2397-7604, DOI 10.1108/JRIT-07-2023-0097.

Chowdhury, E.K., Khan, I.I., & Dhar, B.K. (2023). Strategy for implementing block-chain technology in accounting: perspectives of stakeholders in a developing nation, *Business Strategy and Development*, *6* (3), 477-490, doi: 10.1002/bsd2.256.

Cuello-Garcia, C., P´erez-Gaxiola, G., & van Amelsvoort, L. (2020). Social media can have an impact on how we manage and investigate the COVID-19 pandemic. *J Clin Epidemiol; 127*:198–201. https://doi.org/10.1016/j.jclinepi.2020.06.028.

Daniels, K. N., & Billingsley, K. Y. (2014). Facebook-It's not just for pictures anymore: The impact of social media on cooperative learning. *Journal of Educational Technology, 11*(3), 34-44.

Deaton, S. (2015). Social Learning Theory in the Age of Social Media: Implications for Educational Practitioners, *Journal of Educational Technology, 12*(1), 16. https://doi.org/https://files.eric.ed.gov/fulltext/EJ1098574.

Embarak, O.H. (2022). Internet of Behaviour (IoB)-based AI models for personalized smart education systems, *Procedia Comput. Sci. 203* 103–110, https://doi.org/10.1016/j.procs.2022.07.015.

Fornell, C., & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18* (1), 39-50.

Granic, I., Morita, H., & Scholten, H. (2020). Beyond screen time: identity development in the digital age. *Psychological Inquiry, 31*, 195–223.

Gros, B. (2016). The design of smart educational environments. *Smart Learning Environments, 3*,(15), 1-11.

Grover, P., Kar, A.K., & Dwivedi, Y.K. (2022). Understanding Artificial Intelligence Adoption in Operations Management: Insights from the Review of Academic Literature and Social Media Discussions, *308*, 1–2, https://doi.org/10.1007/s10479-020-03683-9.

Hair, J., Hollingsworth, C.L., Randolph, A.B., & Chong, A.Y.L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems, 117* (3), 442-458, doi: 10.1108/IMDS-04-2016-0130.

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed., Sage, Thousand Oaks, CA.

Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM", *European Business Review, 31* (1), 2-24, doi: 10.1108/EBR-11-20180203.

Hair, J.F.J., Sarstedt, M., Hopkins, L., & Kuppelwieser, V.G. (2014). Partial least squares structural equation modeling (PLS-SEM) an emerging tool in business research. *European Business Review, 26* (2), 106-121.

Haleem, A., Javaid, M., Qadri, M.A., & Suman, R. (2022). Understanding the role of digital technologies in education, *A Review. Sustainable Operations and Computers, 3*, 275-285, doi: 10.1016/j.susoc.2022.05.004.

Hawi, N.S., & Samaha, M. (2017). The relations among social media addiction, self-esteem, and life satisfaction in university students. *Soc Sci Comput Rev*; *35*(5):576–86. https://doi.org/10.1177/0894439316660340.

Hollis, C., Livingstone, S., & Sonuga-Barke, E. (2020). Editorial: The role of digital technology in children and young people's mental health – a triple-edged sword? *Journal of Child Psychology and Psychiatry, 61*, 837–41.

Hosen, M., Ogbeibu, S., Giridharan, B., Cham, T., Lim, W.M., & Paul, J. (2021). Individual motivation and social media influence on student knowledge sharing and learning performance: evidence from an emerging economy. *Computers and Education, 172,* 104262.

Jia, S., Khassawneh, O., Mohammad, T., & Cao, Y, (2023). Knowledge-oriented leadership and project employee performance: the roles of organizational learning capabilities and absorptive capacity, *Curr. Psychol.* https://doi.org/10.1007/s12144-023-05024-y.

Kahveci, N.G. (2015). Pre-service teachers' conceptions on use of social media in social studies education. *International Journal of Progressive Education*, *11*(1), 82-100.

Kaiser, H. F., & Rice, J. (1974). Little Jiffy, Mark IV. *Educational and Psychological Measurement*, *34*(1), 111–117. https://doi.org/10.1177/001316447403400115

Kaliisa, R., Rienties, B., Mørch, A.I., & Kluge, A. (2022). Social learning analytics in computer-supported collaborative learning environments: a systematic review of empirical studies, *Comput. Educ*. Open *3* 00073, https://doi.org/10.1016/j.caeo.2022.100073.

Kim B., & Kim Y. (2017). College students' social media use and communication network heterogeneity: implications for social capital and subjective well-being. *Comput Hum Behav*; *73*:620–8.

Lee, E. (2021). Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom, Biol. *Psychiatry Cogn. Neurosci. Neuroimaging 6* (9) 856–864, https://doi.org/10.1016/j.bpsc.2021.02.001.

Legaree, B.A. (2015). Considering the changing face of social media in higher education, FEMS *Microbiology Letters*, *362* (16), 1e3, doi: 10.1093/femsle/fnv128.

Muro, A., Soler, J., Cebolla, A., & Cladellas, R. (2018). A positive psychological intervention for failing students: does it improve academic achievement and motivation? A pilot study, Learn. *Motiv. 63* 126–132, https://doi.org/10.1016/j.lmot.2018.04.002.

Nadelson, L.S., Berg, W., Fox, B., Grandbouche, P., Harris, M., Kroschel, T.L., & Sandoval, S. (2017). Snap, tweet and post: college student social media perceptions and heutagogic practices and uses. *Int J Higher Educc*, *6*(4):11–27. https://doi.org/10.5430/ijhe.v6n4p11.

O'Brien, L. (2012). *Six ways to use social media in education*, available at: https://cit.duke.edu/blog/2012/04/six-ways-to-use-social-media-in-education/

Pittman, M., Reich, B. (2015). Social media and loneliness: why an Instagram picture may be worth more than a thousand Twitter words. *Comput Human Behav*; *62*: 155–67. https://doi.org/10.1016/j.chb.2016.03.084.

Samaha, M., & Hawi, N.S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Comput. Human Behav*. *57* (2016) 321–325, https://doi.org/10.1016/j.chb.2015.12.045.

Sekaran, U., & Bougie, R. (2016). *Research Methods for Business A Skill-Building Approach.* 7th Edition, Wiley & Sons, West Sussex.

Tandoc, E.C., Ferrucci, P., & Duffy, M. (2015). Facebook use, envy, and depression among college students: is facebooking depressing? *Comput Human Behav*; *43*, 139–46. https://doi.org/10.1016/j.chb.2014.10.053.

Tobias, S., & Carlson, J.E. (1969). Brief report: Bartlett's test of sphericity and chance findings in factor analysis", *Multivariate Behavioral Research*, *4* (3), 375-377, doi: 10.1207/s15327906mbr0403_8.

Whelan, E., Golden, W., & Tarafdar, M. (2022). How technostress and self-control of social networking sites affect academic achievement and wellbeing, *Internet Res*. *32* (7) 280–306, https://doi.org/10.1108/INTR-06-2021-0394.

Young, L., Kolubinski, D.C., & Frings, D. (2020). Attachment style moderates the relationship between social media use and user mental health and wellbeing, *Heliyon 6* (6) e04056, https://doi.org/10.1016/j.heliyon.2020.e04056.

Z. Ali, Z., Gongbing. B., & Mehreen, A. (2018). Understanding and predicting academic performance through cloud computing adoption: a perspective of technology acceptance model, S*pringer Berlin Heidelberg 5* (3), https://doi.org/10.1007/s40692-018-0114-0.

Zhao, L. (2021). The impact of social media use types and social media addiction on subjective well-being of college students: a comparative analysis of addicted and non-addicted students. *Comput Hum Behav Rep*; *4.* https://doi.org/10.1016/j.chbr.2021.100122.

Zhu, Z.T., Yu, M.H., & Riezebos, P. (2016). A research framework of smart education. *Smart learning environments, 3*(1), 4. https://doi.org/10.1186/s40561-016-0026-2