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The Mediating Role of Smart Learning Environment in the Relationship Between Social Media and Academic Performance Among University Students

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Abstract

This study sought to determine the extent to which social media influence the academic performance among university students via smart learning as a mediator. A positivism research philosophy and cross-sectional survey design guided the study. A convenience sampling technique was used to select a sample size of 458 respondents. Primary data was collected using a self-administered questionnaire and analyzed using descriptive and inferential statistics. Partial least squares-structural equation model (PLS-SEM) was employed to analyze the structural model and determine the direct connections between the different constructs. The results establish that social media has a positive and significant effects on academic performance and smart learning environment (($\beta = 0.396$, $t = 6.568$, $p < 0.000$; $\beta = 0.576$, $t = 8.923$, $p < 0.000$) respectively). Simultaneously, smart learning environment had a positive and significant direct effect of academic performance among university students ($\beta = 0.646$, $t = 9.75$, $p < 0.000$). The study concluded that social media significantly influenced the academic performance of university students in Kenya. The study recommends that, university policy-makers need to prioritize investments on social media platforms and enhance smart learning environment within the institutions of higher learning. This can be achieved by deliberately allocating substantial resources towards adoption of the appropriate educational technological innovations, faculty technological skills development and enhancement of digitization of university academic services.

Keywords: *Social media, smart learning environment, academic performance, university students.*

Introduction

Due to the rapid advances in information and communications technology and ubiquitous internet access, the use of social media is like an addiction and has become an integral part of human life every day. As useful tools of communicating and learning, currently, 5.22 billion users which is around 63.8% of global population are actively engaged with social media platforms and spends, on average 2 hours and 23 minutes per days (Statista, 2024, Prioridata,2025). Facebook remains the largest social media platform, with over 3.15 billion monthly active users followed by YouTube with over 2.5 billion active users. Instagram has over 2 billion active users, making it the fourth largest social media platform. TikTok has surpassed 1 billion active users, becoming one of the fastest-growing social media platforms (Prioridata, 2025). The use of social media in the education industry and particularly higher education has soared to top priority due to abundance of cutting-edge learning opportunities for university students to access course content and interact among peers and professional (Ansari & Khan, 2020).

Statement of the Problem

In recent times, the ubiquity of social media platforms has gained immense popularity among university students and significantly transformed our daily lives, including how we communicate, interact and access information (Shahzad *et al.*, 2024). Furthermore, there is an upsurge of digital media tools such as smartphones for educational purpose (Legaree, 22015). The literature on the correlation between social media usage and academic success among students is fast growing, but still limited and primarily focuses on students in the United States (Astatke *et al.*, 2021). This trend can be attributed to several factors, including the ability of these platforms to facilitate access to online tutorials, lectures and educational materials, web-based resources and offering a source of entertainment (Zhao & Zhou, 2021).

Extant literature provide policy directives aimed at fostering a balanced digital ecosystem to bolster academic success among university students (Chowdhury, *et al.*, 2023). Despite this growing adoption of social media platforms like Facebook (Meta) with over 3.15 billion active users per month, YouTube with over 2.8 billion active users, Instagram which has over 2 billion active users and TikTok which has surpassed 1 billion active users and fastest growing social media platform (Prioridata, 2025), a glaring research gaps still exists. The impact of social media, especially in this digital era on academic performance remains under-explored particularly in developing countries, while the mediating role of smart learning environment in the relationship between social media and academic performance remains under-researched in Kenya. To address these research gaps, the study purposed to explore how social media's influence academic performance of students in the university through smart learning environment. The investigation is guided by four research hypotheses.

Research Hypotheses

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

i. Social media (SM) significantly affect the academic performance (AP) of university students?

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

iii. Smart learning environment significantly influence the academic performance of university students?

iv. Smart learning environment mediate between the relationship of social media and academic performance among university students?

Literature Review

This section provides the theoretical, empirical and conceptual framework that guided the study.

Theoretical Review

For the foundation of this study, cognitive load theory (CLT) is harnessed to construct a rigorous theoretical scaffold that connect social media to academic performance. CLT postulates that, every learning materials causes cognitive load on human working memory which has limited capacity and may be overloaded if presented with much information (Sweller, 2011). The evolutionary reaction to such circumstances is to back away and retreat to safer and familiar environment (Islam *et al.,* 2020). This evolutionary mechanism still affects human behavior today and is at play, especially when acquiring new knowledge and information (Panksepp, 2013).

Cognitive load theory is conceptualized to constitute three components; intrinsic load, extraneous load and germane load (Dejong, 2010). Intrinsic load cannot be manipulated and are traced through element interactivity, which can be described as the presence or absence of reference to other learning elements (Islam *et al.*, 2020). Actually, it is the load resulting from processing this information and is affected by individuals' psychological state of mind as well as the prior knowledge (Sweller, 2011). Extraneous cognitive load is undesirable, more often investigated and does not contribute to learning (Mutlu-Bayraktar *et al.,* 2019). It relates to instruction under which cognitive demands can be set to low or high (Hameed *et al.*, 2022). The germane load is a subconscious load that results from the working memory transferring information to long-term memory into the so-called schemas (Sweller, 2011).

Originally introduced as a theory for instructional sciences, CLT has recently been integrated with human-computer interaction (Hollender *et al.,* 2010), and has been widely adopted and succeeded in explaining human online behaviour such as retention in online courses (Mutlu-Bayraktar *et al.*, 2019) and the effect of social media usage on learning (Lau, 2017). With the current ubiquity of social media which entails images, texts, graphs and videos, and massive adoption of smart mobile devices, there is more utilization of extraneous cognitive load and hence less space available for intrinsic and germane load (Hameed *et al.*, 2022). Moreover, since the cognitive capacity remains the same, using it on excessive social media activities leads to cognitive resources wastage and reduced space for other important undertakings. This motivated the anchoring of this current study on CLT.

Empirical Literature Review

The Scenario of Social Media in Kenya

The advent of the digital revolution that has brought ubiquity of social media has become an integral part of daily life for billions of people, transforming our daily lives, including how we connect, access information and communicate with each other (Shahzad *et al.*, 2024; Hu *et al.*, 2023), and its impact on modern society cannot be ignored. Social media sites like Facebook (Meta Platform), Instagram, YouTube, X (Twitter), Snapchat, LinkedIn, TikTok etc., have evolved beyond mere virtual meeting places to become robust ecosystems for learning, collaboration and information dissemination (Shafiq & Parveen, 2023; Modi & Zhao, 2021). From urban center to rural areas, their active influence can be felt everywhere.

In Kenya, the use of social media has grown rapidly in recent years. In year 2024, Kenya was ranked first in the world in terms of time spent on social media platform, where individuals' social media usage stood on average of three hours and forty-three minutes every day. This is an hour and thirteen minutes longer than the average amount of time spent on social media platforms by internet users worldwide each day (Digital, 2024).

This is attributed to Kenya's internet penetration rate which stands at 64.94% of the country's total population, with users ranging between the age of 16 to 64 years old (Statista, 2025).

Despite this tremendous growth, the scenario of social media in Kenya has come with a lot of dynamics. The Gen Z protests in June, 2024 that demonstrated the power of digital activism in mobilizing citizens to demand for political leadership accountability. The spread of fake news and misinformation has become a major concern, with some individuals and groups using social media to spread rumors and propaganda (Owino, 2024). There have been instances of hate speech and cyberbullying which have led to calls for greater regulation and control of social media in the country. Social media has also played a positive role in Kenya, particularly in terms of the Gen Z digital activism and protest for proper governance and social justice (Omoruyi, 2025). The scenario of social media in Kenya is complex and multifaceted.

Social Media and Academic Performance

Academic performance is a crucial element of higher education system (Mufassirin *et al.*, 2023), and different types of academic performance indicators have been used by researchers such as acquisition of knowledge for self-growth (Alamri *et al.*, 2020), life skills (Tus, 2020), academic grades (Zhoc *et al.*, 2019), study habits (Tus, 2020), among others. In the recent times, the impact of social media platforms on academic performance among university students is hotly debated (Chowdhury, 2023). Some researchers such as Oye *et al.*, (2012) Ravizza *et al.*, (2014), argue that excessive use of social media sites for non-academic purposes has detrimental effect on classroom performance. Farrell and Brunton, (2020), advance the same argument by claiming that social media usage decrease study time, disrupt concentration and increase procrastination, hence contributing to poor academic outcomes. In contrast, some recent studies underscore the potential of social media usage in enhancing academic discussion, collaboration, improving grades and consequently bolstering academic performance (Shafiq & Parveen, 2023; Alshuaibi *et al.*, 2018). Other studies have revealed that time spent on social media sites is an important predictor of academic performance and achievement among students in tertiary education (Alamri *et al.*, 2020; Alwagait *et al.*, 2015). Therefore, this study focuses on investigating the influence of social media usage on the academic performance of university students in Kenya.

Mediating Role of Smart Learning Environment

Smart learning entails the convergence of emerging digital technologies such and artificial intelligence, social media among others (Shahzad *et al.*, 2024). They reconfigure higher education landscapes into a more transformative, effective and efficient learning ecosystem (Allal-Ch´erif, *et al.*, 2021), hence empowering students with unprecedented access to educational resources, collaborative platforms and personalized feed-back loops and self-directed learning (Samaha, 2016). Recently, institutions of higher learning are leveraging smart learning environment to bolster students' engagement, foster collaborative ecosystems, strengthen academic performance (Boer *et al.*, 2021) and enhance dynamic and efficient learning ecosystems (Bolick & daSilva, 2024). These interventions exert some positive impact on students' academic performance and as a result universities are leaping technological dividend of smart learning making education ecosystem more inclusive and hence amplify students' academic potential (Shahzad *et al.*, 2024). In light of this advances, the study sought to investigate the mediating role of smart learning environment on the relationship between social media and academic performance among university students (as shown in Figure 1).

Conceptual Framework

A conceptual framework is a model of how one theorizes or makes logical sense of the relationships among the several variables that have been identified as important to the research problem (Sekaran & Bougie, 2016). A diagrammatically representation of the variables explored by this study is shown in Figure 1.

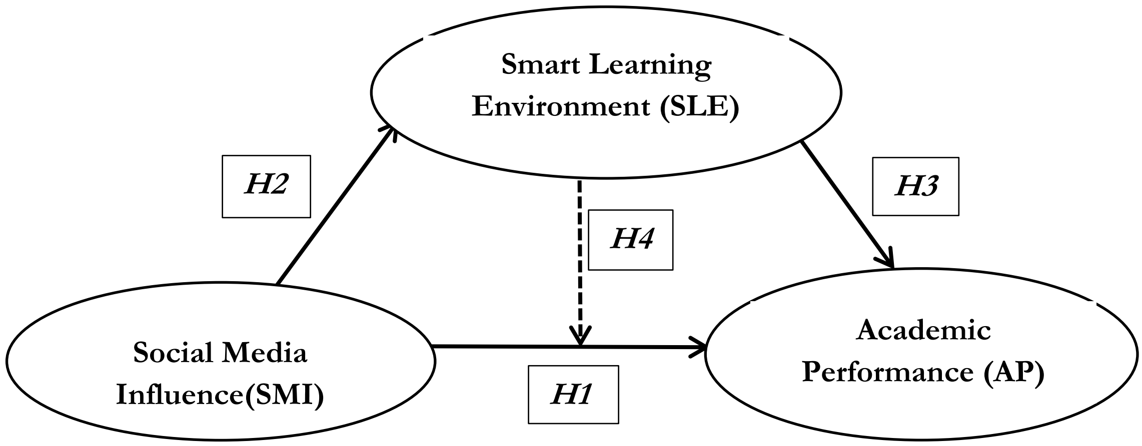

Figure 1: Conceptual Model

Research Methodology

Measurement

The study used a cross-sectional design to collect data using convenience sampling. A structured self-administered questionnaire was used to achieve the intended study's objectives. The instrument of data collection was divided into two components, i.e. sections A and B. Section A comprised of demographic information of the respondents and section B about measurement scales for the three main constructs-social media influence, smart learning environment and academic performance. 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.

Sample and Data Collection

The respondents were selected from several different classes within the university. After classes were identified, the instrument was distributed during class time after approval from the instructors incharge of the classes. The unit of analysis were the students who 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. Approximately 500 questionnaires were distributed and completed within the month of December, 2024. The researcher received 475 responses with a response rate of 91.2% and 458 were useable after data cleaning. The internal reliability was validated using Cronbach's alpha. For the analysis of the data, statistics were performed using IBM SSPS AMOS version 26. In addition, structural models' fit was assessed using the overall model fit indices, which consist of chi-square ($\chi2$)/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

The results section is discussed in two parts. The first part highlights the validation of the model through the reliability and validity measures of scales and model fitness. Whereas, the second part represents the testing of hypotheses through SEM.

Respondent Profile

The data was gathered through a survey from the students of different schools. The sample consisted of 458 respondents, of who, 192 (41.92%) were male and 266 (68.08%) were female. Concerning the education levels, 306 (66.81%) were in undergraduate level and 152 (33.19%) in graduate level. 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.

The respondents' data is summarized by calculating the mean, standard deviation (SD), skewness and kurtosis of academic performance, smart learning environment and social media influence. Table 1 shows the descriptive statistics of the study variables. Smart learning environment has the highest mean value of 3.643 and social media influence has a low mean value of 3.121. On the other hand, academic performance has less variation which indicates a standard deviation of 0.604, and smart learning environment has more variations which is indicated by a standard deviation of 0.700. The study further assessed the instruments for Skewness and Kurtosis. The test results also demonstrate that the values of Skewness and Kurtosis were within their cutoff value -2 to +2 (Tabachnick & Fidell, 2001) and -7 to +7 (Byrne, 2010) respectively.

Table 1

Descriptive Statistics

Construct	Mean	SD	VIF	Skewness	Kurtosis
Academic Performance	3.446	0.604		-1.246	2.400
Smart Learning Environment	3.643	0.700	1.716	-1.388	2.498
Social Media Influence	3.121	0.632	1.716	-0.660	0.925

Sample Adequacy Test

The Bartlett's test of sphericity was significant (*p*-value 0.000), in accordance with conventional practices, and the Kaiser–Meyer–Olkin (KMO) measure of sample adequacy (KMO) was 0.894 (> 0.70), demonstrating that the correlations between the variables are considerably distinct from zero. It is advised that the two statistical values (KMO measure and Bartlett's Test of Sphericity) meet specified minimal conditions before performing a factor analysis (Table 2).

Table 2

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.894
Bartlett's Test of Sphericity	Approx. Chi-Square	3804.395
	df	120
	Sig.	0.000

Measurement Model

The study examined the adequacy of the measurement model by calculating its reliability, convergent validity and discriminant validity. Table 3 shows that all Cronbach's alpha values and composite reliability (CR) values were above 0.70, reflecting a high reliability within the study scales (Fornell & Larcker, 1981). The standardized factor loads for each item and average variance extracted (AVE) for each construct were assessed to determine the convergent validity, and ideally, these values will exceed 0.50 for both. The study test results show that the standardized factor loads (>0.50) and AVE (>0.50) were within their cutoff value, suggesting adequate convergent validity (Hair *et al.*, 2014).

The internal consistency of the data instrument was assessed through Cronbach's alpha value and composite reliability to confirm the reliability of the items. As shown by the data (Table 3), the Cronbach's value was 0.810 for social media influence, 0.871 for smart learning influence and 0. 892 for academic performance and composite reliability scores of 0.812, 0.873 and 0.892 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 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, academic performance (0.79), smart learning environment (0.765) and social media influence (0.709), which were greater than the correlation values among the competing constructs. As shown in Table 4, the discriminant validity of each variable exceeded 0.7, thereby fulfilling the Fornell-Larcker criterion as suggested by Hair *et al.*, (2017).

Table 3

Measurement Model Results

Constructs	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Social Media Influence		**0.810**	**0.812**	**0.502**
SMI1	0.712			
SMI2	0.588			
SMI3	0.680			
SMI4	0.782			
SMI5	0.773			
SMI6	0.680			

Smart Learning Environment		**0.871**	**0.873**	**0.585**
SLE1	0.744			
SLE2	0.656			
SLE3	0.828			
SLE4	0.861			
SLE5	0.869			
Academic Performance		**0.892**	**0.892**	**0.624**
AP1	0.754			
AP2	0.787			
AP3	0.853			
AP4	0.863			
AP5	0.845			

To verify the proposed measurement model, extracted factors from EFA were tested using CFA (maximum likelihood method) with IBM SPSS-AMOS software. The test statistics were as follows; CMIN/DF=2.307, GFI= 0.905, CFI=0.911, NFI= 0.907 and TLI=0.914. All these measured indices fulfilled the recommended thresholds for fitness indices (CMIN/DF < 5, GFI, CFI, NFI, TLI >0.9). RMSEA = 0.076, 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 4

Discriminant Validity-Fornell-Larcker Criterion

Construct	AP	SLE	SMI
Academic Performance	**0.790**		
Smart Learning Environment	0.660***	**0.765**	
Social Media Influence	0.397***	0.576***	**0.709**

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.*, 2010). 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. The results revealed that there is significant direct effect of social media influence (SMI) on academic Performance as shown in Table 5, supporting hypothesis *H1*.

Table 5

Direct Path Analysis for Hypothesis one

Hypothesis	*β*- value	*T*- value	*P*- value	Decision
H1 SM I > AP	0.396	6.568	0.000	Support

Similarly, there was significant effect of social media influence(SMI) on smart learning environment (SLE)(β = 0.576, *t* = 8.923, *p* < 0.000) and smart learning environment (SLE) on academic performance (AP) (β = 0.646, *t* = 9.75, *p* < 0.000), supporting *H2* and *H3* as shown in Table 6.

Table 6

Overall Path Analysis

Hypothesis		*β*- value	*T*- value	*P*- value	Decision
H1	***SMI > AP***	***0.25***	***0.44***	***0.660***	***No Mediation***
H2	SMI > SLE	0.576	8.923	0.000	Support
H3	SLE > AP	0.646	9.75	0.000	Support

Mediation Analysis

The study explored the mediation role of smart learning environment on the relationship between social media influence and academic performance. The results demonstrated that, the direct correlation effect between social media influence and academic performance decreased from (β = 0.396, t = 6.568, p < 0.000) as shown in Table 6 to (β = 0.25, t = 0.447, p < 0.660) indirect effect with insertion of smart learning environment as a mediator as shown in Table 8-overall path analysis. The results indicate that smart learning environment has no significant mediation relationship between social media influence and academic performance. H4 is not support as shown in Table 6.

Discussion of Results

The primary aim of this research was to find out how social media influence academic performance among university students' in Kenya considering smart learning environment as a mediator. The findings of the research reveal that social media positively and significantly affects the academic performance of university students despite its intrusive nature that has raised concerned (Boahene et al., 2019). Therefore, this study affirms the utility of social media as a tool for knowledge-sharing and collaborative learning (Mirzakhani et al., 2022). This conforms with prior results of Shahzad et al. (2024), Khaola et al. (2022), Hussin (2022), Hosen et al. (2021) and Chang et al. (2019), who reveals that social media positively impact university students' academic performance.

Moreover, the study also demonstrates that smart learning environment have a mediating role between social media and students' academic performance. Smart learning involves personalized, adaptive learning experiences (Smart et al., 2021). According to Clarke (2020), factors like effective learning strategies, high levels of engagement, and abundant educational resources contribute to positive trends. This aligns seamlessly with prior studies highlighting the influence of smart learning on social media usage (Shahzad et al., 2024, Allal-Ch´erif, et al., 2021, Muro, et al., 2018). This study not only affirms but also enhance the extant literature on the relationship between social media and academic performance in the age of smart learning environment.

Conclusion

The study examined student perceptions of the influence of social media on academic performance through smart learning environment in Kenyan university students. The results revealed three significant findings. First, students believe social media has a significant effect on the academic performance of Kenyan students. Second, students believe social media significantly enhance smart learning environment. Third, students believe smart learning environment positively impacts the academic performance. In conclusion, this study advances a compelling theoretical and empirical foundation for university policy formulation when it comes to social media platforms, smart learning environment and students' academic performances. The university administrators are provided with elaborate, evidence-based framework to guide on adoption of human-centered technological innovations for technology-enhanced education and its managerial and practical implications.

Recommendations

To improve students' academic performance, universities should prioritize allocating funds to acquire social media technologies, develop faculty technological skills, improve smart learning environment and create or update the social media usage policies. The codes of conduct also need to be updated to address the potential negative externalities such as cyberbullying, privacy breaches and misinformation. Policy-makers also need to explore partnerships with technology firms to further democratize access to emerging social media technologies hence improving the students' performance and enhance retention levels.

Limitations and Future Research

Although this present study has numerous recommendations, the study also has some limitations that needs to be acknowledged in future studies. First, this study used a quantitative method for data analysis, but qualitative as well as mixed method can also be a very effective tool to understand a more in-depth individual experience of social media influence on academic performance. Second, the limited sample size may not be representative of the entire population of university students in Kenya. Third, this study used social media in general. In the future, one can specify a particular type of social media, i.e. Facebook (Meta), WhatsApp, or Zoom app, Google classroom, Google meet, etc. Fifth, the five-point Likert scale questionnaire was used to collect data, but for more accurate and reliable results, a seven-point Likert scale might be used. Finally, similar studies could be conducted by including other age groups besides university students or by examining other universities in Kenya in particular and other countries in the region in general.

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