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# Generative Artificial Intelligence and Academic Performance: Mediating Role of Smart Learning Environment

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**Abstract**

The purpose of the study was to investigates the relationship between generative artificial intelligence (GAI), academic performance (AP) and smart learning environment (SLE) as a mediator. A convenience sampling technique was used to select a sample size of 456 respondents. Primary data was collected using a self-administered questionnaire and analysed using descriptive and inferential statistics. Partial least squares-structural equation model (PLS-SEM) was employed to analyse the structural model and determine the direct connections between the different elements. The results establish that generative artificial intelligence has a positive and significant influence on smart learning environment and academic performance ($\beta = 0.523$, $t = 10.178$, $p < 0.000$); $\beta = 0.387$, $t = 7.353$, $p < 0.000$ respectively). Simultaneously, smart learning environment partially mediates between the generative artificial intelligence and academic performance among university students ($\beta = 0.06$, $t = 1.19$, $p < 0.234$). The results of this study contributes to the current academic discourse on technology-enhanced education by showing that generative artificial intelligence have a positive impact on students' academic performance.

**Keywords**: *Generative artificial intelligence, smart learning environment, academic performance, university students.*

## Introduction

In the contemporary volatile, uncertain and dynamic world, our society is progressively embracing a vast radical technological transformation that permeates every facets of life from politics, economic, sociocultural and even in education arena (Ocaña,Valenzuela & Garro, 2019). This trend towards adapting to emerging technological paradigms has spawned an array of technologies known as "Virtual assistants." According to Yang, Zhuang and Pan (2021), these virtual assistants employ computer algorithms to mimic human intelligence, creating an illusion of interaction with another human being, a phenomenon collectively known as field of "artificial intelligence (AI)." In the 21st century, artificial intelligence has unlocked and unleashed a profound potential in the human ecosystem (Kumar *et al.*, 2024) which has emerged as a powerful revolutionary force that is transforming various industries including educational section.

In recent time, the penetration of this artificial intelligence have significantly transformed our daily lives, including how we interact, communicate and access information and particularly among young generation for whom the integration of AI and social media has become nothing short of indispensable in both their education and daily experiences (Shahzad *et al.*, 2024). In the education sector, this penetration is reshaping the way we teach, learn and interact with information and learners are also experiencing a profound shift in their daily approaches to education (Ou, 2024). The integration of AI in modern approach to education holds the promise to revolutionize traditional education paradigms by introducing innovative tools capable of creating new frontier of personalized learning, enhanced academic outcomes, greater accessibility to quality education and foster interactive learning environments for learners worldwide (Ou, 2024).

According to Ou (2024), the infusion of GAI and education is transcending the boundaries of traditional classroom setting. E-learning platform are utilizing AI-driven tools to enhance academic outcomes by automating administrative tasks, providing real-time feedback to learners, providing accessibility to information which empowers students in decoding complex subject matters (Fauzi *et al.,* 2023), increasing students' learning speed (Singh, Visishta & Singla, 2024), sharpening problem- solving acumen and facilitating real-life engagement and collaboration among students and teachers across geographical boundaries (Shahzad *et al.,* 2024). This rise of AI powered intelligent tutoring systems, chatbots and virtual assistants is also redefining the role of educators, enabling them to focus on fostering creativity and innovation, critical thinking and problem-solving skills while leaving routine tasks to AI assistants (Zhai *et al.*, 2021).

## Statement of the Problem

Extant literature and several previous studies such as Abulibdeh et al., (2024); Shahzad et al., (2024); Singh et al., (2024) and Ou., (2024), predominantly addresses the technical and pedagogical dimensions of generative artificial intelligence on education, a glaring research gap exists on the behavioral aspects of students' interaction with generative artificial intelligence tools like ChatGPT in modern digitized education era. Hence, this research aims to bridge this critical gap by exploring the significant relationships among generative artificial intelligence, academic performance and the mediating role of smart learning environment among university students in the Kenyan educational context.

## Research hypotheses

The aim of this study was to test the following hypotheses:

i. Generative artificial intelligence has a positive significant effect on students' academic performance.
ii. Generative artificial intelligence has a positive and significant effect on smart learning environment.
iii. Smart learning has a positive and significant influence on students' academic performance.
iv. Smart learning has a positive and significant influence on students' academic performance. Strategic leadership ethical practices do not significantly influence the organizational performance of pharmaceutical companies in Kenya.

## Literature Review

### *Generative Artificial Intelligence and Academic Performance*

Artificial intelligence has emerged as a transformative force that is reshaping the education landscape, driving unprecedented changes in teaching methodologies, bolstering students learning outcomes and reducing the workload among educators and learners (Zhai et al., 2021). Furthermore, as artificial intelligence advances, new applications in education such as generative artificial intelligence platforms appear which create a ground-breaking possibility for understanding student difficulties, foster group creativity, streamline pedagogical processes, streamline administrative operations and optimizing student learning outcomes by offering tailored materials and relevant comments (Chen et al, 2020).

With educational institutions incorporating generative artificial intelligence learning into their curricula, artificial intelligence literacy has become increasingly crucial and ignited educational debate for educators to stay abreast of the development in the field. This is expected to democratize access to education and help fully realize the potential of AI technologies (Singh et al., 2024). However, to tap the full capabilities of generative AI for education particularly in specific context, more extensive research and development are necessary to leverage GAI's advantages in education settings. A critical aspect of this endeavour is understanding the impact of generative artificial intelligence on academic performance among university students. Consequently, this study posit the following hypothesis-generative artificial intelligence has a positive significant effect on students' academic performance (as shown in Figure 1).

### *Generative Artificial Intelligence and Smart Learning Environment*

Recent rapid developments in artificial intelligence in higher education (HE) has emerged as a transformative technology with a wide-range of applications such as; creating educational content, generating personalized recommendations and assisting in instructional design (Bolick & daSilva, 2024). Furthermore, the adoption and integration of generative artificial intelligence in higher education has the potential to enhance teaching and learning by automating tasks, personalizing instruction, expanding the accessibility of education resources, transform teaching methods and enriching learning experiences.

To prepare students for industry and global leadership, universities have a responsibility to provide their students with up-to-date efficient and relevant smart technologies and devices (Wood & Moss, 2024) and respond to the rapidly changing technological landscape (Chan & Hu, 2023). This will enable universities to provide equitable education to all students and generative artificial intelligence is seen as being able to assist in such provision. Curriculum content and pedagogical practices at the universities also needs to be revised and updated in light of recent generative artificial intelligence paradigm shift (Bearman et al., 2023). According to Thurzo et al., (2023), universities educators are generally slow to adapt to new technologies due to resistance to changing teaching practices and hence posit the following hypothesis-generative artificial intelligence has a positive and significant effect on smart learning environment (as shown in Figure 1).

### *Smart Learning Environment and Students' Academic Performance*

Students learn in different ways. Some prefer facts, data and experiments whereas others prefer principles and theories. Some prefer reading written material whereas others prefer problem solving. However, the learning management systems in most of the educational institutions have been developed with the philosophy of "one-size fits all" and as a result, most students tend to get disoriented and the information overload results in reduced efficiency. Smart learning is a paradigm of technology-enhanced education environment which emphasizes the use of smart technologies, smart pedagogies and technological design in reconfiguring educational landscapes into a more dynamic and efficient learning ecosystem (Li & Wong, 2021). This pedagogical evolution utilizes the latest technical and social advancements to facilitate effective customized, interactive learning experiences (Chen, et al., 2021). As an emerging mode of education environment, smart learning has the potential to foster and empower students with unparalleled access to educational contents, methods, evaluations, personalized feedback loops and environments, thereby enriching self-directed learning (Hwang & Choi, 2016).

According to Shahzad et al, (2024), educational institutions are leveraging smart learning to bolster student engagement, foster collaboration ecosystems, and strengthen academic performance. Universities, in particular, are seizing the technological dividend of smart learning to advance students' skills acquisition and foster inclusive education that amplifies student academic potential (Zhang et al., 2020). Although the advocacy of smart learning is a global interest, this study grounds its argument in the context of a developing economy, Kenya, and hence posits the following hypothesis—Smart learning has a positive and significant influence on students' academic performance (as shown in Figure 1).

### *The Mediating Role of Smart Learning Environment*

According to Samaha (2016), smart learning environments empower students with unprecedented access to educational resources, collaborative platforms and personalized feed-back loops, hence enriching self-directed learning. Recently, institutions of higher learning are leveraging smart learning 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 seizing the technological dividend of smart learning to more engagement and inclusive education systems that amplify students' potential (Shahzad et al., 2024). Furthermore, research by (Chen, et al., 2021) underscores the pivotal role of artificial intelligence-driven smart learning in augmenting students' academic performance. In light of this advances, the following hypothesis has been formulated—Smart learning environment mediates the relationship between generative artificial intelligence and academic performance (as shown in Figure 1).

## Conceptual Framework

Conceptual frameworks are maps inferred or derived from specific illustrations or circumstances that aid in demonstrating the relationships between an interplay of variables graphically and diagrammatically (Hennink *et al.,* 2020). A diagrammatically representation of the variables explored by this study is shown in Figure 1.

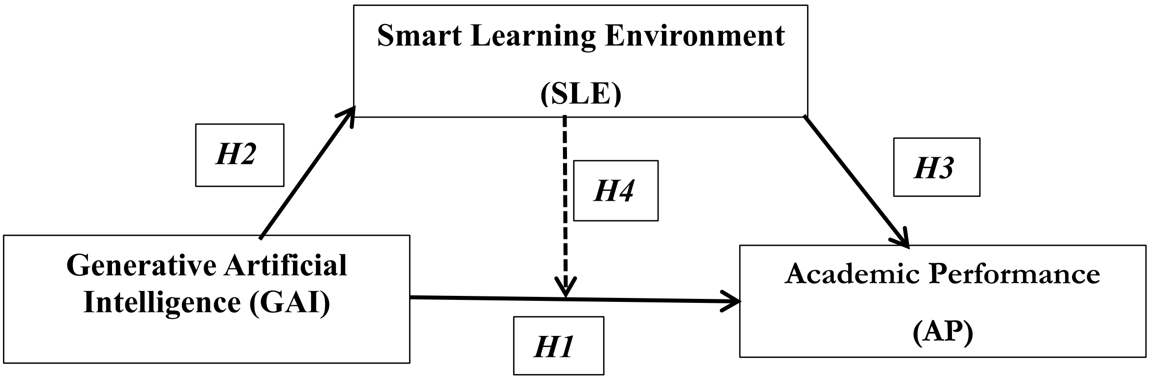


**Figure 1:** *Conceptual Framework*

## Research Methodology

### Measurement

The study used valid and reliable measurement items via a self-administered questionnaire survey with a well-structured closed-ended questionnaire formulated to achieve the intended study's objectives. The questionnaire was dissected into two sections, i.e. sections A and B. Section A consisted of 5 demographic questions such as age, gender, education level, internet usage per day and current degree program major. Similarly, section B consisted of three major constructs—generative artificial intelligence, smart learning environment and students' academic performances, which have been taken from different previous studies. All the constructs were tested using close-ended 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 research design for the study was a quantitative cross-sectional survey using primary data that was collected through a constructive face-to-face administered questionnaire. Due to the indeterminate size of university students' population, the study adopted a convenience sampling technique. This technique was chosen because it allows for easy data collection from a specific population that may be difficult to reach through other sampling techniques. The target population of the study were university students both in undergraduate and postgraduate levels who pursued different programs in different schools such as Technology, Health Science, Arts and Social Science, Business and Management. The university students as the unit of analysis were considered appropriate for the study based on their active engagement with emerging technologies and the fact that they spending long hours on the internet for academic and problem-solving purposes. The study primarily centered on a single, reputable international university that offers prominent and diverse fields of study. By doing so, the aim was to include a diverse range of communities, nationalities and cultures in the sample. 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. A total of 500 questionnaires were distributed 470 completed questionnaires were returned and 456 were valid for analysis after a rigorous screening for missing values, multivariate outliers, and unengaged responses. This sample size aligns with guidelines suggesting that empirical research should involve more than 30 but fewer than 500 participants (Roscoe, Lang & Sheth, 1975). The survey was conducted within the month of December, 2024.

### Data Analysis

The researcher used the highly effective IBM statistical software SPSS and Smart PLS Structural Equation Model (SEM-AMOS) for the descriptive and inferential data analysis, respectively. SEM is used to confirm the reliability and validity of the data and illustrate theoretical relationships between the variables (Anderson & Gerbing, 1988). Additionally, it aids in the evaluation of construct interactions and construct-indicator relationship in a single model (Hair et al., 2016). SEM was also used because it goes beyond the limits of the conventional multivariate statistical techniques such as regression and correlation, to assess the final measurement model, ensures that the theoretical model fit the data and analyses relationship between one or more independent and dependent variables.  Sample size, as well as a researcher's biases, does not affect the application of this software (Hair et al., 2017).

### Sample Adequacy

Deciding whether a data set is acceptable for principal component analysis, two major concerns must be considered; sample size and the degree of the link between the components (Pallant, 2020). According to Barclay et al (1995), as a rule of thumb, they propose 10 times the number of items in the most complex construct or 10 times the number of structural paths directed at a particular construct in the inner model. In either scenario, the sample size obtained from 450 respondents is adequate for factor analysis. However, for rigor of assessing the strength of the relationship between the components, the correlation matrix, Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were adopted as suggested by Tabachnick and Fidell (2007). According to Kaiser and Rice (1974), the KMO measure test and Bartlett's test of sphericity was conducted to check and decide whether it was appropriate to advance with the factor analysis of the collected data set.

## 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%0 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's of business administration (MBA), 39 (8.52%)  master's of science in management of information system (MSc-MIS), 52

(11.25%) master's 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.

**Table 1**

*KMO and Bartlett's Test*

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.912 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 4540.449 |
| | df | 120 |
| | Sig. | 0.000 |

### *Measurement Model*

The measurement model serves as a rigorous framework for exploratory factor analysis and testing the reliability, validity and confirmatory factor analysis. To identify the predominant items in the designed instrument, exploratory factors analysis was conducted using rotation under the principal component analysis method. The loadings of items were investigated and all items had factor loadings of more than 0.60, which is an acceptable threshold recommended in multivariate-analysis literature (Hair *et al.*, 2019). This outcome indicates a robust association between items and underlying constructs.

On the reliability front, the internal consistency of the variables in the measurement model was assessed using Cronbach's alpha and composite reliability (CR). As evidenced by the data, each variable had a satisfactory level of internal consistency. Cronbach's values were 0.903 for generative artificial intelligence, 0.871 for smart learning environment and 0.892 for academic performance of the students exceeding the minimum threshold of 0.60 (Hair *et al,* 2017). similarly, composite reliability values were 0.905 for generative artificial intelligence, 0.872 for smart learning environment and 0.892 for academic performance which exceeded 0.7, indicate a good reliability.

Next, the assessment of convergent validity was done using the average variance extracted (AVE). The AVE values for generative artificial intelligence, smart learning environment and academic performance were 0.614, 0.583 and 0.624 respectively. These findings exceed the minimum threshold for AVE confirming convergent validity. Discriminant validity was assessed using Fornell and Larcker's criterion (As shown by Table 2), which ensures that each variable is distinctly separate from all others within the measurement model. The square roots of the AVE of constructs were 0.784 for generative artificial intelligence, 0.764 for smart learning environment and 0.790 for academic performance which were greater than the correlation values between each constructs and all other variables.

**Table 2**

*Discriminant Validity*

| Construct | GAI | AP | SL |
|---|---|---|---|
| Generative Artificial Intelligence (AI) | **0.784** | | |
| Organizational Performance | 0.388*** | **0.790** | |
| Smart Learning Environment (SL) | 0.523*** | | **0.764** |

*The discriminant validity of each variable exceeded 0.7, thereby fulfilling the Fornell-Larcker criterion as suggested by Hair et al. (2017).

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.

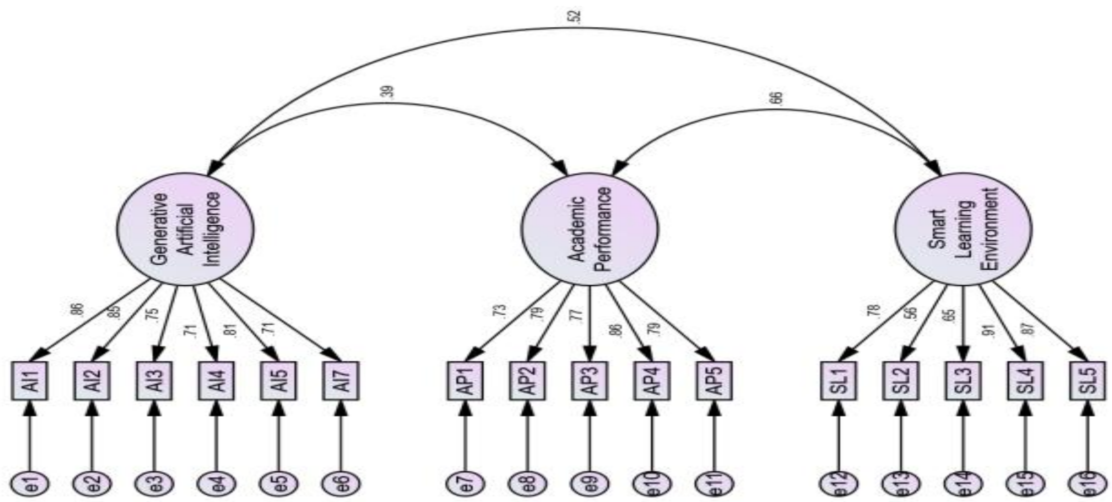

**Figure 2:** *Measurement Model*

The test statistics were as follows; CMIN/DF=2.556, GFI= 0.917, CFI=0.952, NFI= 0.932 and TLI=0.942 as shown in Table 3. All these measured indices fulfilled the recommended thresholds for fitness indices (CMIN/DF < 5, GFI, CFI, NFI, TLI >0.9). RMSEA = 0.075, 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 3**

*Summary Statistics for Model Fitness Indices*

| Model Measures | CMIN/DF | RMSEA | GFI | CFI | NFI | TLI |
|---|---|---|---|---|---|---|
| Model score | 2.556 | 0.075 | 0.917 | 0.952 | 0.932 | 0.942 |

***Structural Equation Modeling and Hypotheses Testing***

SEM is a statistical approach used to investigate the relationship between variables and verify the proposed model. It entails investigating the direct and indirect influences of constructs on one another, as well as evaluating the model's overall structure. To analyze the hypotheses, a structural analysis was performed using PLS-SEM as shown in Figure 3.

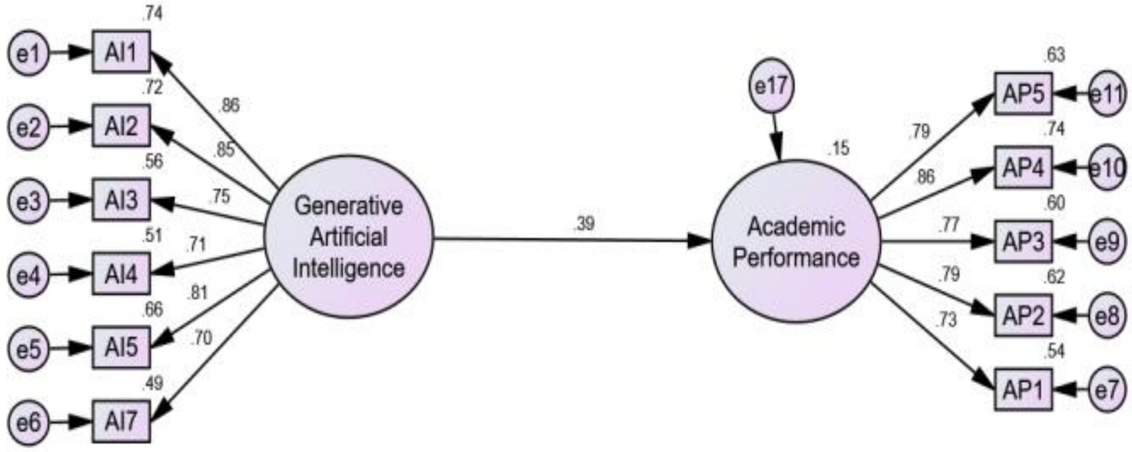


***Figure 3:*** *Structural Model*

After conducting a rigorous evaluation of the reliability and validity tests through the measurement model, structural model was worked on using PLS-SEM. The fitness of the measurement model was assessed using different indices, including 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). The results are CMIN/DF=2.62, RMSEA=0.076, GFI= 0.938, CFI=0.962, NFI= 0.948 and TLI=0.951. All fulfill the recommended thresholds for the fitness indices (CMIN/DF < 5, GFI, CFI, NFI, TLI >0.9 and RMSEA <0.08) (Hair et al., 2019) as shown in Table 4.

**Table 4**

*Model Fitness Indices for Measurement Model*

| Model Measures | CMIN/DF | RMSEA | GFI | CFI | NFI | TLI |
|---|---|---|---|---|---|---|
| Model score | 2.62 | 0.076 | 0.938 | 0.962 | 0.948 | 0.951 |

The hypothesized structural relationships and path coefficient for hypothesis one is given in Figure 3. The results reveals that there is a significant, direct effect of generative artificial intelligence (GAI) on students' academic performance (AP) ($\beta = 0.387$, $t = 7.353$, $p < 0.000$) supporting H1, as shown in Table 5.

**Table 5**

*Path Analysis for Hypothesis One*

| Hypothesis | β- value | *t*- value | *P*- value | Décision |
|---|---|---|---|---|
| H1 GAI-> AP | 0.387 | 7.353 | 0.000 | Support |

Similarly, significant, direct effect of generative artificial intelligence (GAI) on smart learning environment (SLE), ($\beta = 0.523$, $t = 10.178$, $p < 0.000$) supporting H2. Furthermore, the results revealed a significant, direct effect of smart learning environment (SLE) on students' academic performance (AP), ($\beta = 0.628$, $t = 10.115$, $p < 0.000$) supporting H3 as shown in Table 7.

The study also examined the mediating role of smart learning environment between generative artificial intelligence and students' academic performance as shown in Figure 4. Table 6 exhibits the structural equation model fit indices. According to the goodness-of-fit statistics, the structural model adequately explained the data. The test statistics were as follows; CMIN/DF=2.556, RMSEA=0.075, GFI= 0.917, CFI=0.952 and NFI= 0.932. All fulfil the recommended thresholds for the fitness indices (CMIN/DF < 5, GFI, CFI, NFI >0.9 and RMSEA <0.08) (Hair et al., 2019).

**Table 6**

*Model Fitness Indices for Overall Structural Model*

| Model Measures | CMIN/DF | RMSEA | GFI | CFI | NFI | TLI |
|---|---|---|---|---|---|---|
| Model score | 2.556 | 0.075 | 0.917 | 0.952 | 0.932 | 0.942 |

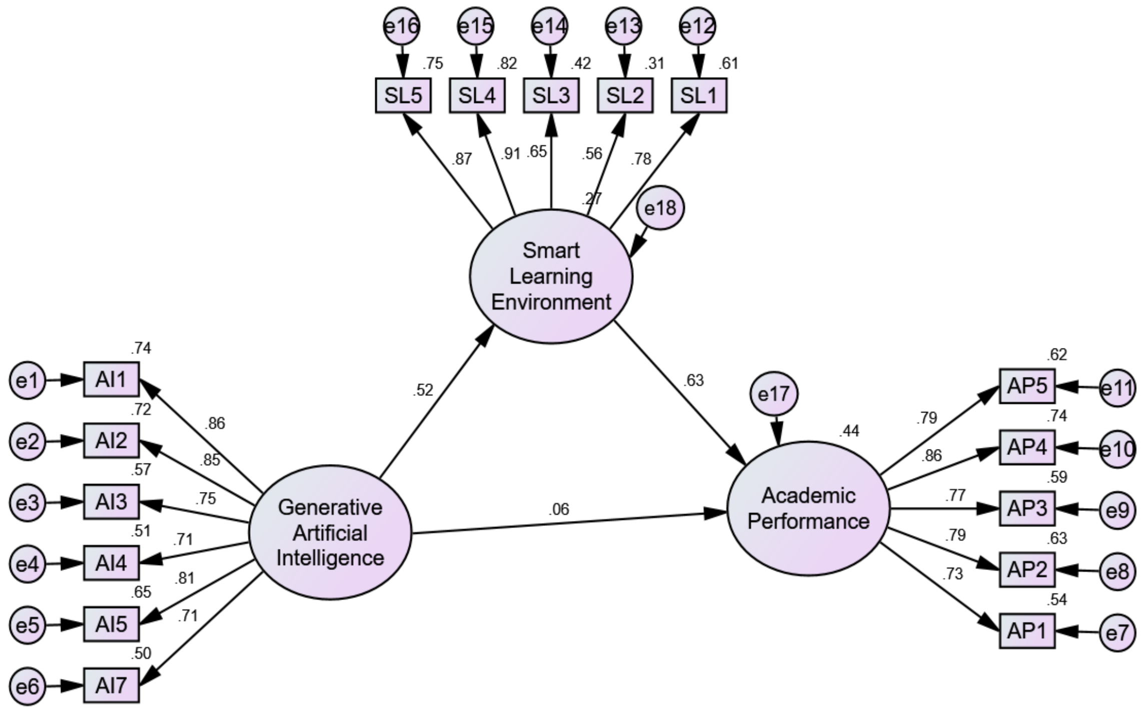


**Figure 4:** *Overall Structural Model*

In the case of H4, the results reveals that smart learning environment positively mediates the relationship between generative artificial intelligence and students' academic performance ($\beta = 0.06$, $t = 1.19$, $p < 0.234$) supporting H4 as shown in Table 7.

**Table 7**

*Overall Path Analysis*

| Hypothesis | β- value | *t*- value | *P*- value | Décision |
|---|---|---|---|---|
| H2 GAI > SLE > | 0.523 | 10.176 | 0.000 | Support |
| H3 SLE > AP | 0.628 | 10.115 | 0.000 | Support |
| H4 GAI > SLE > AP | 0.06 | 1.19 | 0.234 | Support |

**Discussion of Results**

Firstly, generative artificial intelligence as an emerging technology has become a transformative agent, redefining paradigms in education sector and interpersonal communication arena motivating this study. The overall outcomes of this study present strong evidence for hypothesis one (H1), demonstrating a positive significant relationship between generative artificial intelligence and academic performance among university students. These findings resonate with prior research (Zhahzad et al., 2024; Kamalov et al., 2023; Ramo et al., 2022). This hypothesis acceptance on the use of generative artificial intelligence improving teaching and learning experiences is becoming increasingly important in the education arena. As a result, university students are embracing technologies such as GAI since they suit well on the needs and specification of academic assignment work (Shahzad et al., 2024). secondly, the increased focus on digitalization and technology-enabled education in global arena has made university students highly receptive to cutting-edge tools in enhancing learning outcomes and improving education experiences.

Secondly, integration of generative artificial intelligence is revolutionizing the learning environment by enhancing human-machine collaboration, enabling personalized, adaptive and experiential learning, and preparing university students with skills and adaptability needed for the future workforce (Shailendra et al., 2024). The overall outcomes of this study present strong evidence for hypothesis two (H2) and clearly demonstrate a positive significant relationship between generative artificial intelligence and smart learning environment. The finds agree with prior research (Shahzad et al., 2024; Pal & Patra, 2021; Al-Mamary et al., 2020). Acceptance of this hypothesis posits that, most universities have been making significant investments in digital transformation and technology infrastructure. As a result, students have become aware and appreciative of cutting-edge technology such as GAI, which provides solutions for school assignments.

Thirdly, the integration of diverse technologies into educational environments serves to bolster and enhance collaborative interactions between university students and academics (li & Wong, 2021). Researchers in the field of higher education have recently initiated several studies into the integration of smart technologies into conventional pedagogical methods, aiming to augment student's learning experience and outcomes (Zhahzad et al., 2024). Smart learning as an emerging technological advancement, when integrated with diverse pedagogical strategies has the potential to provide an innovative educational environment aimed at enhancing students' educational encounters and knowledge acquisition (Gros, 2016). The overall outcomes of this study present strong evidence for hypothesis one (H3), demonstrating a positive significant relationship between smart learning environment and generative artificial intelligence among university students. These findings resonate with prior research by Zhahzad et al., (2024). Therefore, university administrators need to pay more attention to smart learning environment to enhance collaboration and students' academic performances.

Lastly, this study overall outcomes demonstrates that, smart learning environment plays a strong positive and significant mediating role on the relationship between generative artificial intelligence and academic performance among university students (H4). This finding is consistent with prior research which demonstrated that smart learning has a significant and positive mediating impact on the relationship between generative artificial intelligence and academic performance (Zhahzad et al., 2024). Therefore, it is important for university policy makers to ensure a robust smart learning systems are in place for effective and efficient preparation of students for the job market. In conclusion, this study present a compelling evidence-based empirical foundation for policy formulation touching on the nexus between generative artificial intelligence, smart learning environment and academic performance in the era of digital transformation of education sector. Moreover, the study aims to support and catalyze concrete actionable shift in the pursuit of appropriate human-centric technology adoption.

## Conclusion

The study sought to determine the nexus between generative artificial intelligence and academic performance with mediating role of smart learning environment. The results reveals that there is a significant, direct effect of generative artificial intelligence on students' academic performance ($\beta = 0.387$, $t = 7.353$, $p < 0.000$). Similarly, there was significant, direct effect of generative artificial intelligence on smart learning environment ($\beta = 0.523$, $t = 10.178$, $p < 0.000$). Furthermore, the results revealed a significant, direct effect of smart learning environment on students' academic performance ($\beta = 0.628$, $t = 10.115$, $p < 0.000$).

## Recommendations

The recommend actionable insights to various stakeholders, including educational institutions administrators, policymakers and educators, on the benefits of incorporating generative artificial intelligence tools into the teaching and learning process. For higher educational institutions administrators, the empirical findings equip their institutions with the tools to incorporate generative AI on the development of more effective AI-integrated curricula and support systems, ultimately enhancing student engagement and thereby enhance the academic outcomes and successes. The educators gain insights into how to integrate generative AI tools in their teaching practices much better, making the educational experience more responsive, engaging and dynamic. Moreover, the study will serve as a practical guide for students on how to strategically deploy GAI for their academic successes.

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