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Generative Artificial Intelligence and Mental Well-Being of University Students. A Structural Equation Modeling (SEM) Based- Analysis

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Abstract

The emergence and application of generative artificial intelligence (GAI), typified as ChatGPT and others have the potential for significant impact on the mental well-being. However, there is currently a lack of systematic research on GAI on mental well-being particularly among university students in Kenya. The purpose was to conduct an exploratory study on the relationship between generative artificial intelligence and mental well-being (MWB) among university students in Kenya. The study used convenience sampling technique. The data was collected from 458 respondents using a structured, closed-ended, self-administered questionnaire. It was analyzed through partial least squares structural equation modeling (PLS-SEM), which is frequently used for prediction models. The model was further checked for goodness-of-fit using Amos. The findings of this study establishes that generative artificial intelligence has a positive and significant influence on mental well-being (β = 0.129, t = 1.997, p < 0.046) among university students. These revelations contribute to the discourse on technology-enhanced education, showing that embracing GAI can have a positive impact on student mental well-being. The study recommends the university administrators to prioritize investment in generative artificial intelligence technologies with the view of enhancing students' mental wellbeing as they undergo their university education.

Keywords: *Generative artificial intelligence, mental well-being, university, students.*

Introduction

Artificial intelligence (AI) has significantly evolved in the over years and one of its groundbreaking advancements lies in the development of generative artificial intelligence (GAI) (Chakraborty *et al.,* 2024), typified by ChatGPT (Shahzad *et al.,* 2024) from Open AI, which is a large language model (LLMs). While early analytical AI applications (e.g., forecasting the Estimated Time of Arrival of your delivery or predicting which TikTok video to show next) were based on algorithms that mimic human intelligence and perform tasks that typically require human cognitive abilities (Zirar *et al.*, 2023), generative artificial intelligence extends far much beyond these capabilities (Lim *et al.,* 2023). Specifically, generative artificial intelligence which represents a natural extension of deep learning (Chang & Park, 2024) is able to create original (e.g., musical) content (Baidoo-Anu & Ansah, 2023), realistic creative work, human-like texts (Martinelli, 2022), lifelike characters in video-games, virtual assistant in education (Eysenbach, 2023) among others. Owing to these essential nature and capabilities, generative artificial intelligence has found applications across important fields such as healthcare (Liu *et al.*, 2023), education ecosystems (Shahzad *et al.*, 2024), art and entertainment (Kirk & Givi, 2025) among others.

A recent report by Goldman Sachs (2023) reveals that, generative artificial intelligence has a potential to drive global GDP by 7% (or almost US $ 7 Trillion), and lift the productivity growth by nearly 2.5% by 2033 (EY, 2024). The market size is forecast expected to show an annual growth rate (CAGR 2025-2030) of 41.5%, resulting in a market volume of US$ 356.05 Billion by 2030 (Statista, 2024). Moreover, on 30th November, 2022, Open AI officially released ChatGPT version 1.0 to public and managed to hit a million users within 5 days and currently grown to over 250 million users weekly (Intelliarts, 2025), while it took Meta (formerly Facebook) 300 days, X (formerly Twitter) 720 days, and Instagram 75 days to reach the same milestones (Biswas, 2023). This made it the most rapidly growing, widely used, and industry-spanning digital product in history, demonstrating the popularity and powerful influence of ChatGPT (Cao *et al.,* 2023).

Statement of the Problem

In Greek mythology, Pandora opened a box that was left in the care of her husband, and whirlwind of dark forces surfed it and inadvertently released myriad troubles and curses upon the world (Redahan & Kelly, 2024). The advent of every new form of technology raises similar fears today, and the recent emergence, tremendous adoption and application of generative artificial intelligence has conformed firmly to this pattern and amplified concerns worldwide about its impact on individuals and society at large. The reactions towards the same ranges from quiet curiosity to outright panic.

As already discussed in mass media (Economist, 2023), academic books (Suleyman & Bhaskar, 2023; Kissinger *et al.,* 2021) and scientific research papers (Sindermann *et al.,* 2021; Schepman & Rodway, 2020; Zastudil et al*.,* 2023), the impact of generative artificial intelligence is widespread and complex. And the integration of generative artificial intelligence into higher education is revolutionizing the way teaching and learning is conducted (Song *et al.,* 2024), marking a shift towards a new generation of pedagogical tools, mirroring the arrival of milestones like the internet (Song *et al.,* 2024). However, despite the rapid proliferation and adoption of generative artificial intelligence technologies in a variety of educational contexts and content (such as, generating personalized recommendation, creating educational content or assisting in instructional design) (Bolick & da Silva, 2024), pedagogical strategy execution to fully realize its potential is lacking (Al-Mamary *et al.*, 2024) and its effectiveness within the education settings raises concerns (Su & Yang, 2023; Lim *et al.*, 2023; Pedersen, 2023). The

Lack of academic research on the effect of GAI on pedagogical, learning outcomes and mental well-being exacerbate the gap (Al-Mamary *et al.*, 2024).

While extant literature and several previous studies such as (Alharbi, 2023; Barret & Pack, 2023; Cooper, 2023; Dempere *et al.,* 2023; Mahapatra, 2024; Ng, *et al*., 2024; Rice *et al.,* 2024; Van Wyk, 2024) predominantly addresses the technical and pedagogical dimensions of generative artificial intelligence on education settings, a clear research lacuna exists on the impact of generative artificial intelligence technologies on mental well-being of university students' in modern digitized education era. Hence, this research aims to bridge this critical gap by exploring the significant relationships between generative artificial intelligence and mental well-being among university students in the Kenyan educational context.

Research Question

The aim of this study was to the research question:

> *RQ1*. How does generative artificial intelligence (GAI) influence mental well-being (MWB) of university students as shown in Figure 1:

Literature Review

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

Theoretical Review

This paper attempt to address the highlighted research gaps by leveraging the well-established uses and gratification (U & G) theory, which was first articulated by Elihu Katz in (Katz, 1959). The theory is an audience-centric approach that focuses on people's behavior in communication media, rather than the media's behavior toward people (Sutanto *et al..,* 2013). However, in recent times, U&G theory has played a more key role in comprehending how individuals embrace and interact with state-of-the-art technologies, such as generative artificial intelligence (Lee & Cho, 2020), virtual reality (Kim *et al.,* 2020), and augmented reality (Rauschnable, 2018). The theory assumes that individuals' hedonic and utilitarian needs motivate them to adopt a tool for information seeking (Luo *et al.,* 2011). Hedonic needs can be referred to as one's emotional desires while utilitarian needs are associated with one being rational, cognitive and task driven (Anderson *et al.,* 2014).

On the other hand, the theory asserts that users actively seek media sources that best fulfil their specific needs (Katz e*t al.*, 1973). This assertion is based on the principle that (i) media users actively choose the media they consume and (ii) they are fully conscious of their reasons for choosing one from many media options. U&G theory further postulates that media consumption by a user is typically intentional and purposive and that users energetically seek to satisfy their needs (Reychav & Wu, 2014). In this light, the theory is considered a suitable theoretical framework for this current research for two main reasons: (i) University students actively choose the GPTs technologies for their academic and social activities (ii) the students are fully conscious of why they choose GPTs platforms for such activities instead of other social media platforms such as Meta (Formerly Facebook), X (Formerly Twitter), YouTube, TikTok, Google, etc (Wang, 2023). Uses and gratification theory also provides a theoretical lens that helps discover users' attitudes toward these technologies and the intentions to use (Ruggiero, 2000).

Empirical Review

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 and platforms such as GPTs have paved the way for digital media to become a prominent method for social interaction, access to information and content sharing (Gawrych, 2022; Cuello-Garcia, *et al.,* 2020). Moreover, the phenomenon of shifting between platforms and emerging technologies has been noted in research with UK-based university students as 'transferal between devices' for its addictive potential (Conroy *et al.*, 2023).

The integration of generative artificial intelligence into higher educational ecosystems transcends mere scholastic achievements (Shahzad *et al.*, 2024), since it holds the promise of significantly enhancing learning experiences but also challenges to learner social connectedness and mental well-being (Dawoodbhoy *et al.,* 2021). Javaid, *et al.,* (2023) unearthed the myriad ways in which generative artificial intelligence can act as a positive force in the mental well-being among individuals by providing emotional support, alleviating stress, facilitating self-reflection, and deploying personalized interventions. Therefore, navigating this new frontier, educators must strike a balance between leveraging generative artificial intelligence platforms advantages and safeguarding the emotional and mental well-being of the learning communities to ensure that GAI's integration in higher education is beneficial, ethical, and truly transformative (Zewude *et al.*, 2024). Taken collectively, these conflicting views and outcomes call for a nuanced evaluation of the intricate relationship between generative artificial intelligence media and mental well-being particularly in the universities in the Kenyan context.

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.

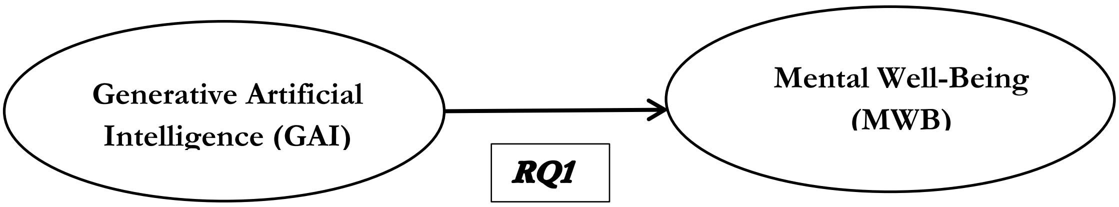

Figure 1. *Conceptual Model*

Research Methodology

Measurement

This current study focused on both undergraduate and graduate students in different schools in an international private university in Kenya. The study utilized purposive sampling technique to ensure that respondents fulfilled predetermined criteria and represented a range of demographics. Data was gathered through self-administered questionnaires with a well-structured close-ended questions formulated to achieve the intended study's objectives as recommended by Sekaran and Bougie (2016). 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 main constructs of the study, which had 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. Potential respondents were briefed on research objectives and then requested to participate in the survey with assurance of anonymity and confidentiality to minimize social desirability

Sample and Data Collection

To realize a good response rate for the study, 500 questionnaires were distributed. The respondents were selected from several different classes in different schools 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 respondents were on the research objectives and then requested to voluntarily participate in the survey with assurance of anonymity and confidentiality to minimize social desirability bias (Sun & Wang, 2020). Once agreed to participate, they were given between 5 and 10 minutes to fill the questionnaire. Out of the 500 questionnaires distributed, 475 were obtained and 458 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.

Results and Findings

Respondent Profile

The sample frame of the study consisted of the students from an international private university in Kenya. A total of 500 questionnaires were distributed to the students via face-t-face method. However, 475 respondents were documented, out of which 458 respondents were complete and usable. Overall, 41.92% (192) of the respondents were men, whereas 68.08% (266) were women. Concerning the education levels, 66.81% (306) were undergraduate students, while 33.19% (152) were post graduate students. In terms of ages, 154 (33.77%) were within 17 to 21 years age brackets, 192 (42.11%) ranged between 22 to 27 years, 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, skewness and kurtosis of generative artificial intelligence (GAI) and mental well-being (MWB). Table 1 demonstrate the descriptive statistics of the study variables. Generative artificial intelligence has the highest mean value of 3.543 and mental well-being has a low mean value of 3.090. On the other hand, mental well-being has less variation which indicates a standard deviation of 0.713, and generative artificial intelligence has more variations which is indicated by a standard deviation of 0.830. The construct normality test was confirmed via Skewness and Kurtosis. The values stayed within the permissible range of -2 to +2 (Tabachnick & Fidell, 2001) and -7 to +7 (Byrne, 2010), respectively. Furthermore, multicollinearity was evaluated using correlation coefficients and variance inflation factor (VIF). The VIF between the two constructs was 1.234, which was below the acceptable limit of 3.3 (Kock, 2015), denoting no multicollinearity.

Table 1

Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Generative AI	3.543	0.850	-0.780	0.640
Mental Well-Being	3.090	0.713	-0.447	0.425

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. As presented in Table 2, the value is 0.877 indicating the sample data was adequate to conduct EFA. To check the non-zero correlation among the study variables items, Barlett's test of sphericity was considered appropriate. This study test result shows 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.

Table 2

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.877
Bartlett's Test of Sphericity	Approx. Chi-Square	2741.545
	df	66
	Sig.	0.000

Measurement Model

As presented in Table 4, the internal consistency of the variables in the applied model was assessed through Cronbach's alpha value and composite reliability to confirm the reliability of the items. The Cronbach's value was 0.903 for generative artificial intelligence and 0.856 for mental-well-being and composite reliability scores of 0.907 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.,* (1998) and Nunnally and Bernstein (1994). This exemplify a robust internal consistency.

The convergent validity of the measurement model was depicted by standardized loading of each construct as well as the average variance extracted (AVE). The AVE values for generative artificial intelligence and mental-well-being were 0.613 and 0.505 respectively. All measurement items exceeded the minimum threshold of 0.5, thereby 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 4.

Table 4

Psychometric Properties of Measures

Constructs	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Generative AI		**0.903**	**0.904**	**0.613**
GAI1	0.872			
GAI2	0.868			
GAI3	0.809			
GAI4	0.772			
GAI5	0.843			
GAI7	0.764			
Mental Well-Being		**0.856**	**0.859**	**0.505**
MWB1	0.762			
MWB2	0.768			
MWB3	0.739			
MWB4	0.839			
MWB5	0.709			
MWB6	0.770			

Construct validity was assessed through convergent and discriminant validity. 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, generative artificial intelligence (0.783) and mental-well-being (0.711), which was greater than its correlation coefficients as shown in Table 5. The discriminant validity of each variable exceeded 0.7, thereby fulfilling the Fornell-Larcker criterion of every construct (Fornell & Larcker, 1981).

Table 5

Discriminant Validity-Fornell-Larcker Criterion

Construct	GAI	MWB
Generative AI	**0.783**	
Mental Well-Being	0.155**	**0.711**

To verify the proposed measurement model, confirmatory factor analysis was conducted to assess the underlying structure of the constructs. The result of CFA indicates two factors along with the 12 items in the proposed model which is represented in Figure 2.

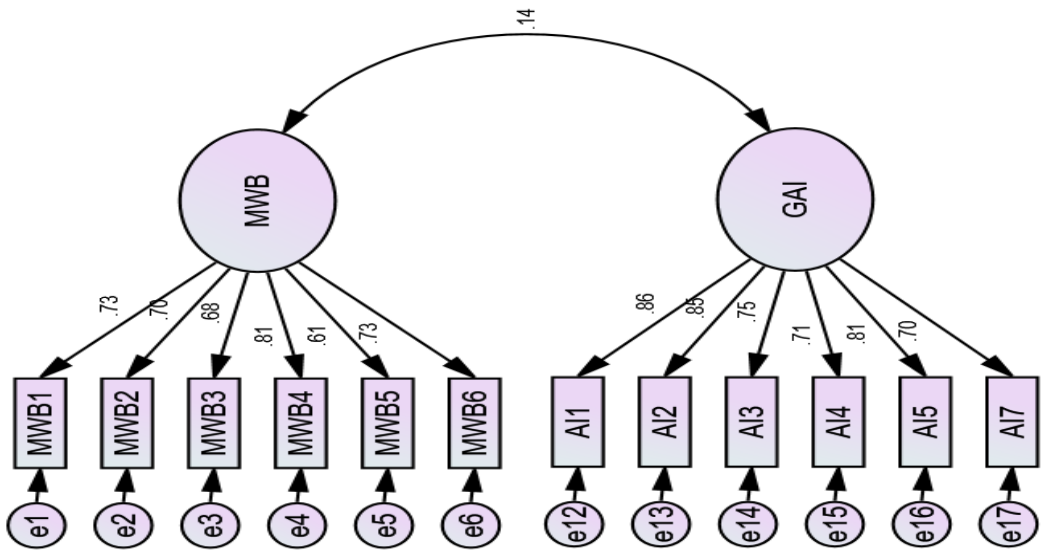

Figure 2. *Measurement Model*

The test statistics were as follows; $\chi 2$/df ratio was 2.485, the Root Mean Square Error of Approximation was 0.041, the Goodness of Fit Index was 0.933, the Normed Fit Index was 0.929, the Tucker Lewis Index was 0.945, and the Confirmatory Fit Index was 0.956 as shown in Table 6. All these measured indices fulfilled the thresholds (CMIN/DF < 3; GFI, CFI, NFI, TLI > 0.9; RMSEA < 0.7) as recommended by Tabachnick, *et al.,* (2007).

Table 6.

Summary Statistics for Measurement Model Fitness Indices

Model Measures	CMIN/DF	RMSEA	GFI	CFI	NFI	TLI
Model score	2.485	0.041	0.933	0.956	0.929	0.945

Structural Equation Modeling and Hypotheses Testing

The structural model was assessed for its adequacy before undertaking path analysis. The analysis indicated the model converged well with the data, as all fit indices met the cut-off values (Schreiber, 2008). Specifically, the $\chi 2$/df ratio was 2.15, the Root Mean Square Error of Approximation was 0.051, the Goodness of Fit Index was 0.925, the Normed Fit Index was 0.918, the Tucker Lewis Index was 0.943, and the Confirmatory Fit Index was 0.954. All the values fulfilled the criteria recommended by Tabachnick, *et al.*, (2007), with $\chi 2$/df below 3, Root Mean Square Error of Approximation below 0.7, and Goodness of fit Index, Normed Fit Index, Tucker Lewis Index, and Confirmatory Fit Index values exceeding 0.9. Additionally, the constructs were assessed for unidimensionality. All measurement items had standardized factor loadings within the range of 0.709–0.872 shown in Table 4. These loading are significant at $p < 0.001$, indicating the constructs' unidimensional.

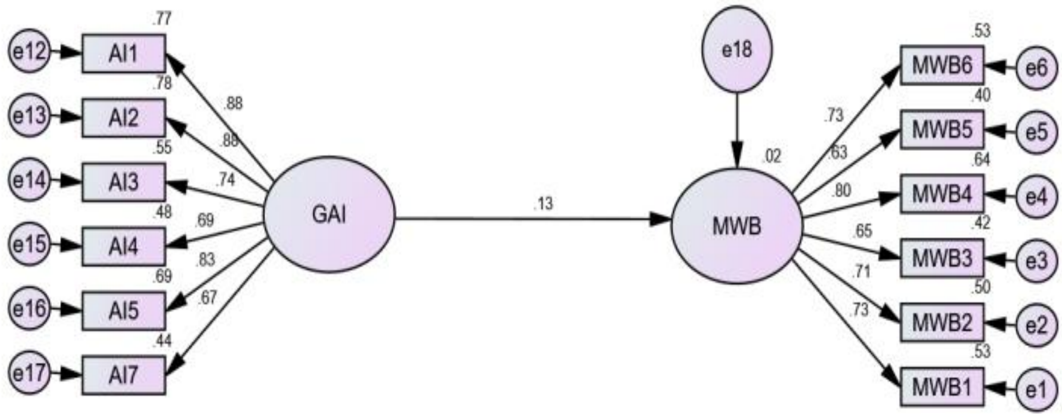

Figure 3. *Structural model*

To assess the hypothesis of this research, SEM was used to analyze the association between exogenous and endogenous variables. The hypothesized overall structural relationships and path coefficients are demonstrated in Figure 3. The results revealed that students perceived a positive and significant relationship between generative artificial intelligence (GAI) and mental well-being (MWB) ($\beta = 0.129$, $t = 1.997$, $p < 0.046$). Thus, *H1* is unequivocally supported, as shown in Table **7.**

Table 7

SEM Results

Hypothesis	*β*- value	*T*- value	*P*- value	Results
GAI > MWB	0.129	1.997	0.046	Significant

Discussions

ChatGPT has led the revolutionary development and integration of generative artificial intelligence into the fabric of modern life and gradually shifted the paradigms of applications in different sectors such as education to interpersonal communications (Shahzad, *et al.,* 2024) and healthcare (Liu, *et al.,* 2023; Sallam, *et al.,* 2023). The advancements have brought invaluable benefits but also raised critical questions about their impact of generative artificial intelligence on mental well-being. Recognizing the magnitude of these concern, the primary aim of this current study was to rigorously investigate students' perceptions of the generative artificial intelligence and its influence on mental well-being among university students in Kenya context. The findings of the research reveal that generative artificial intelligence positively and significantly affects the mental well-being ($\beta = 0.129$, $t = 1.997$, $p < 0.046$) of university students, hence answering the research question *(RQ1).* This conforms with the prior results of Mousavi *et al.*, (2023) and Shahzad *et al.,* (2024), which revealed that generative artificial intelligence enhances mental well-being. Therefore, university administrators and policymakers need to pay more attention to generative artificial intelligence technologies to enhance emotional support and mental resilience, hence mitigating feelings of isolation and loneliness (Young *et al.*, 2020).

Conclusions

This current study sought to explore how generative artificial intelligence impact mental well-being in Kenyan university students. The result reveals that, generative significantly affects students mental well-being. Therefore, the study offers a compelling, evidence-based framework to navigate the complex landscape of emerging technologies choices and adoption. The policy guide not only contributing to academic discourses but bolster the confidence of adopting emerging technologies to enhance learning outcomes. Despite skepticism, the promise of generative artificial intelligence in education sector and students mental-well being is becoming increasingly attractive, as it can address universal issues and increase engagement with learning activities.

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 generative artificial intelligence and mental well-being. Second, the limited sample size may not be representative of the entire population of university students in Kenya. Third, this study used generative artificial intelligence in general. In the future, one can specify a particular type of generative artificial intelligence. Finally, 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.

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