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Effects of Climate Change and Artificial Intelligence on Mental Health and Academic Performance in Kenya

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ABSTRACT

Mental health conditions such as Stress, anxiety, trauma, and existential issues are all made worse by the increased frequency of catastrophic weather events and environmental degradation brought on by climate change. Potential solutions to lessen the negative effects of climate change on mental health are provided by digital advancements, especially artificial intelligence (AI) and digital phenotyping. Access and solution adoption concerns must be carefully considered when integrating digital tools into climate-related mental health care. The objective of the study was to address the effects of climate change on mental health and the scalability of digital interventions through cooperation amongst students. The study adopted a cross-sectional study design targeting college students in the Kisii region, Kenya. The convenience sampling method was used to sample 359 participants who were distributed questionnaires. Variables were examined using partial least squares-structural equation modelling (PLS-SEM), and data analysis was conducted using the specialized statistical programme SmartPLS in conjunction with multiple linear regression and confirmatory factor analysis (CFA). The results demonstrate that students' educational achievement and mental wellness are impacted by both the environment and artificial intelligence (AI). Additionally, the positive effects of AI and climate change on academic performance and mental health are amplified by digital learning, which serves as a positive moderating factor. These findings contribute to the discussion about using technology to improve education by showing how implementing AI and addressing climate change might benefit student performance and well-being.

INTRODUCTION

In recent years, the interconnected issues related to mental wellness and environmental degradation have grown to be significant global concerns for society (Arunachalam & Velmurugan, 2018). Rising temperatures and more frequent extreme weather events have a greater effect on people's mental health. Mental health has been affected by climate change in both direct and indirect ways (Nothling et al., 2024). Extreme weather events such as hurricanes, tornadoes, and wildfires can cause stress, anxiety, and trauma. Environmental degradation on a global scale can exacerbate feelings of worry, loss, and future anxiety. For instance, changing climate patterns make droughts and floods more severe, which disrupts agricultural and food security which resulting in societal discontent and violence. Extreme temperatures have also been associated with adverse mental health consequences, such as a higher incidence of hostility, violence, and suicide.

Climate change contributes to inequality by combining social and economic determinants of health to produce a series of mental health problems. Children, elderly people, communities of colour, low-income areas (especially Indigenous communities), and among the populations who are most vulnerable to mental health problems are climate migrants.

Research has also begun to document an emerging group of climate-specific psychological reactions, which are defined as distress related to school environmental changes that affect the academic achievement of students. The development of artificial intelligence (AI) and the prevalence of global warming have significantly impacted mental health. The next generation, for whom AI and the environment have become integral parts of their daily lives and education, will be most affected by this transformation (Iqba et al., 2022). Despite the importance of these technologies, little is known about how they affect academic performance and mental health together, which necessitates more research.

There are significant ethical concerns with disparities in mental health caused by environmental disasters. Despite contributing less than 4% of the world's carbon dioxide emissions, sub-Saharan African countries have experienced decades of extreme heat, drought, and flood (Green Climate Fund, 2025). According to studies, 50% of flood-displaced people in rural Africa below the Sahara report having anxiety, PTSD, or depressive conditions. These events have devastated millions of people and had a significant psychological impact (Nothling et al, 2024). HICs, which make up around 70% of historical carbon dioxide emissions, have stronger recovery systems and face fewer challenges, underscoring the need to address these inequalities by promoting strategies to develop and integrate mental health programmes and environmental adaptation measures in vulnerable regions.

The climate justice concept holds that, as LMICs contribute significantly to global emissions, HICs have a moral duty to provide economic, technical skills, and policy assistance to mitigate the detrimental consequences on psychological wellness in these countries. Initiatives like the Green Climate Fund (GCF) have provided funding for resilience and climate adaptation (Green Climate Fund, 2025). As of 2024, the GCF has committed $13.5 billion to 243 initiatives in 129 countries, covering countries with low or middle incomes as well as certain high-income ones like Australia (Green Climate Fund, 2025).

Integrating AI into teaching has the potential to improve students' mental health positively in their academic performance. In recent research, artificial intelligence (AI) can enhance mental health in different ways, such as self-reflection, stress reduction, and psycho-social support through the use of customized treatments. ChatGPT and other artificial intelligence (AI) systems can serve as non-judgmental platforms for students to communicate their emotional and neurological situations and difficulties by offering factual support at the same time. AI can lower stress and foster self-awareness, and provide a secure environment for discussing emotional and mental health concerns (Juma et al., 2025).

AI has demonstrated benefits in the medical field, specifically in the identification and treatment of mental health disorders. Artificial intelligence (AI) algorithms are able to look for early indicators of mental illness in various data sets, such as social media activity and electronic medical information. This proactive approach enhances therapy procedures and speeds up intervention, which improves individual results of disorders through a variety of specialized and accessible mental health services offered by artificial intelligence (AI)-powered virtual agents. AI-driven therapies such as psychological education, nonjudgmental listening, and evidence-based therapy strategies might enhance existing approaches and raise the likelihood of successful outcomes by employing AI algorithms to assess treatment-response data.

AI is currently a powerful and unpredictable force in education that greatly improves learning results for every student (Naser et al, 2015). AI improves academic achievement by streamlining administrative processes, providing targeted support systems, and creating personalized learning experiences (Salas-Pilco & Yang, 2022), and state that in order to reap the benefits of AI in education, researchers must overcome challenging issues related to bias, resource constraints, and ethical quandaries. Addressing these difficulties effectively requires cooperation between academics, educators, legislators, and technology developers from various disciplines and stakeholders (Zawacki-Richter et al, 2019). While evaluating the long-term effects of AI technology on student accomplishment and educational success, prior research has emphasized these challenges and provided recommendations for their suitable integration (Tsai et al, 2023).

It is essential to acknowledge the continued importance of the human element in education; instead of taking the place of human mentoring and training, AI instruments should be used to enhance it though (Tsai et al, 2023). The integration of generative AI, such as ChatGPT into educational systems offers a multitude of opportunities to enhance academic achievement (Lanitis, 2023). For instance, by being customized to each student's unique abilities, interests, learning preferences, and individualized learning experiences, which enhance enthusiasm, involvement, and conceptual mastery. Mastery of important subject areas can be facilitated by adaptive learning algorithms, which can identify knowledge gaps and provide focused interventions. Artificial intelligence (AI) can also free teachers from administrative duties so they can spend more time teaching (Arunachalam & Velmurugan, 2018).

Climate change's increasing effects on mental health make it necessary to implement inclusive, intersectional, culturally sensitive, and economical approaches. To address the various vulnerabilities among impacted groups and promote a fair and sustainable recovery process, several strategies are crucial (Andr´e et al, 2018). Culturally sensitive programs, such as incorporating Indigenous methods and providing psychological first aid training to community health workers, can fill important gaps. For interventions to be effective, intersectional vulnerabilities must be addressed. During natural disasters, women, rural dwellers, individuals with impairments, and indigenous groups encounter particular difficulties. Culturally relevant mental health services, inclusive ways to evacuate, and gender-sensitive interventions will all promote recovery pathways. Improving telemedicine, mobile clinics, and healthcare infrastructure in rural locations can help reduce the time it takes to get mental health care.

These computer models are starting to determine which populations could most urgently require mental health care through the integration of geospatial fire data with information on chronic illness, poverty, and mental health treatment accessibility. AI design that takes into account factors like age, disability, and CALD status, for example, may improve mental health outcomes following disasters and expand the technologies' capacity to address inequities (Ma & Huo, 2023). AI-powered mental health treatments are integrated into disaster recovery strategies to guarantee a comprehensive and fair strategy by inclusion of mental health metrics in policy efforts (Salas-Pilco & Yang, 2022). AI can also reduce short-term psychological consequences and promote long-term resilience, particularly for marginalized and disadvantaged individuals. Sustainability, ethical management, and integration must be given top priority as AI is developed for disaster management in order to prevent escalating already-existing inequities.

METHODS

Approach

This study investigates how college students view the impact of electronic platforms on their academic achievement and mental health using a realist research ethic and a deductive technique. In order to collect data for this study, questionnaires were distributed systematically. Scales developed from previous studies and customized for the population were used to measure variables that were used in the study. Using the Likert scale to extract detailed answers that allow the study to determine the degree to which responders are in agreement or disagreement with the given statements.

Sampling

A cross-sectional design was used in the study, and the study chose three educational institutions in Kisii, Kenya, at random to collect data. Since the number of students was unknown, a convenience sampling method was used to choose the participants.

Data Analysis

Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to examine variables and the preferred analytical method for this study because it has been widely used and has shown usefulness in the body of existing literature (Farrukh, 2023), and SEM improves the efficiency and rigor of statistical analysis, leading to better results than traditional statistical methods. Confirmatory factor analysis (CFA) and multiple linear regression were combined in this second-generation regression approach to allow measurement and structural models to be used simultaneously (Shahzad, 2023). This study made use of the specialized statistical program SmartPLS thoroughly to evaluate these models.

Hypotheses of the Study

H1: Academic performance is positively impacted by artificial intelligence, according to students.

H2: Students think that mental health benefits from artificial intelligence.

H3: Students think that academic achievement is positively impacted by climate change.

H4: Students think that mental health is positively impacted by climate change.

H5: Digital learning favorably mediates the effect of AI on students' views of their mental health (H5b) and academic performance (H5a).

H6: Students' perceptions of climate change impact on their academic achievement (H6a) and mental health (H6b) are favorably mediated by digital learning.

RESULTS AND DISCUSSION

Response Rate

A total of 359 questionnaires were distributed to students, and only 324 (90.3%) questionnaires were filled out and returned, while 35 (9.7%) did not respond, which was enough to provide findings with appropriate consistency and dependability (Figure 1).

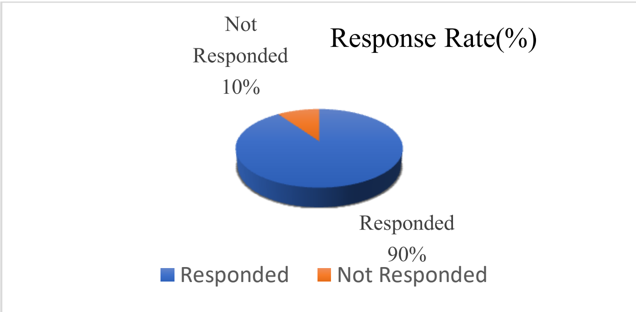

Figure 1. Response Rate

Demographic Characteristics of Participants

Harman's one-factor test using SPSS software to thoroughly assess the possibility of common demographic characteristics (Farrukh, 2023) (Table 1).

Table 1. Demographic characteristics of participants

Demographic		Frequency (n:359)	Percentage (%:100)
Gender	Male	217	60.4
	Female	142	39.6
Age			
	18-21	76	21.2
	22-23	124	34.5
	24-25	117	32.6
	Above 26	42	11.7
Daily internet use			
	1-5 hours	69	19.2
	6-10 hours	153	42.6
	More than 10 hours	137	38.2

A randomly selected group of 359 respondents' demographic data is included in the table, with particular attention paid to gender, age, and daily use of the internet. With 217 male respondents (60.4%) and 142 female respondents (39.6%), the sample is primarily male. If gender plays a substantial role in the research issue, this gender disparity may have an impact on the findings of the research. The majority of the participants, 124 (34.5%), are between the ages of 22 and 23. Closely behind, 117 (32.6%) are between the ages of 24 and 25. Forty-two (11.7%) of the responders are older than 26 years old, while 76 (21.2%) are younger, aged 18 to 21. Given the age range, it is possible that the findings represent the tastes and habits of younger adults, especially those in their early twenties.

The fact that more than 80% of respondents use the internet for more than six hours every day suggests that they are highly engaged with it. This pattern might indicate that the study's target group is heavily reliant on technology, which could influence how they view related subjects. Important information about the sample population can be gleaned from the demographic breakdown. The findings may favor the habits, tastes, and opinions typical of this group, as indicated by the majority of younger adults and the preponderance of males. Furthermore, these respondents' high daily internet usage suggests that they are probably accustomed to digital platforms, which may have an impact on their answers on online preferences, behaviors, and attitudes.

Gender Distribution of Respondents

The study determined the respondents' gender distribution to assess the level of gender disparity and certify the study's representativeness (Figure 2).

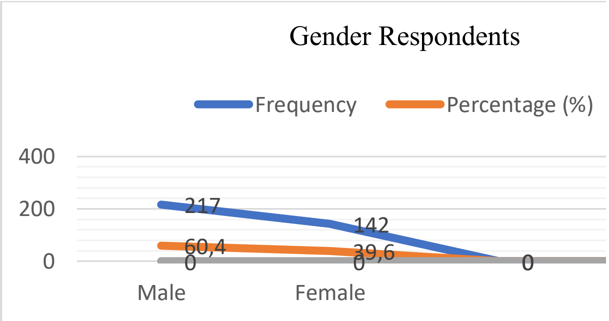

Figure 2. Gender respondents

The Participants' gender was tabulated, and the findings indicated that there were 142 (39.6%) females and 217 (60.4%) males' students.

Discriminant validity

Each variable's discriminant validity was greater than 0.7, as shown in *Table 2*, meeting the requirements (Sarstedt et al., 2022). The HTMT ratio was also used in this study to assess how comparable the latent components were. As shown in *Table 2*, the study validated discriminant validity for every measure, with a standard HTMT range of -1 to 1. All of these HTMT ratios were below 0.85, which complies with recommended standards for discriminant validity. Five constructs were evaluated for discriminant validity using the Fornell-Larcker criterion. Artificial Intelligence (AI), Climate Change (CM), Digital Learning (DL), Academic Performance (AP), and Mental Well-Being (MWB). The results are shown in the table. The Fornell-Larcker criterion ensures that each construct measures a unique concept, which is necessary for discriminant validity.

Table 2. Evaluation of discriminant validity using Fornell-Larcker

Construct	AI	CM	DL	AP	MWB
Artificial intelligence (AI)	0.886				
Climate change (CM)	0.341	0.783			
Digital learning (DL)	0.065	0.577	0.874		
Academic performance (AP)	0.089	0.540	0.411	0.956	
Mental well-being (MWB)	0.091	0.542	0.415	0.961	0.941

The diagonal values represent the square roots of the Average Variance Extracted (AVE) for each construct. AI (0.886): Strong discriminant validity, it is greater than the correlations with CM, DL, AP, and MWB. CM (0.783) indicates good discriminant validity, as it exceeds its correlation with other constructs. DL (0.874) demonstrates distinctiveness, being higher than correlations with other constructs. AP (0.956) exhibits excellent discriminant validity, significantly higher than its correlations. MWB (0.941) has strong discriminant validity, remaining distinct from the other constructs.

The values off the diagonal represent the correlations between the constructs. Off-Diagonal Values (Correlations), AI and CM (0.341), moderate correlation, but AI maintains its distinctiveness. DL and CM (0.577) indicate a stronger relationship, yet DL is still valid as a separate construct. AP and MWB (0.961) very high correlation, suggesting a potential overlap between these constructs, but both still demonstrate strong validity based on diagonal values. In construct Relationships, some correlations exist, particularly between AP and MWB; all constructs are sufficiently distinct from one another. For instance, the correlations between AI, DL, and AP remain low, reinforcing their unique contributions.

The findings from Table 2 suggest that each construct, AI, CM, DL, AP, and MWB, maintains robust discriminant validity, confirming that they measure different theoretical aspects. Although there are moderate correlations among some constructs, particularly between AP and MWB, the overall strong diagonal values indicate that researchers can confidently use these constructs in studies without significant overlap. This distinctiveness enhances the reliability of findings related to these constructs in various research and practical applications.

Table 3 presents correlation values among five constructs: Artificial Intelligence (AI), Climate Change (CM), Digital Learning (DL), Academic

Performance (AP), and Mental Well-Being (MWB). These correlations are crucial for understanding the relationships between constructs and assessing their distinctiveness.

Table 3. Evaluation of discriminant validity using the Heterotrait-Monotrait (HTMT) ratio

Construct	AI	CM	DL	AP	MWB
Artificial intelligence (AI)	-				
Climate change (CM)	0.087				
Digital learning (DL)	0.061	0.603			
Academic performance (AP)	0.099	0.573	0.406		
Mental well-being (MWB)	0.091	0.579	0.406	0.833	-

The values in the table represent the correlations between the constructs, with lower values indicating stronger discriminant validity. AI and CM (0.087) indicate a very low correlation, indicating a strong distinctiveness between AI and CM, suggesting that they measure different constructs effectively. DL and CM (0.603) is a moderate correlation signifies some relationship between digital learning and climate change, indicating that they may influence each other to some extent. AP and CM (0.573) suggest a correlation that academic performance may have some relationship with climate change, but it remains moderate, allowing for distinct measurement.

AP and DL (0.406) is a moderate correlation, indicating that academic performance and digital learning are related, but they still retain their individual constructs. MWB and AP (0.833) is a high correlation between mental well-being and academic performance, suggesting a significant relationship, indicating that these two constructs may overlap considerably in certain contexts. MWB and DL (0.406) indicate the correlation which is moderate correlation, suggesting some relationship but not enough to undermine the distinctiveness of the constructs.

Table 4 summarizes the relationships between various constructs, including their direct and mediation impacts, as indicated by the β-values, standard deviations, t-values, and p-values. The results provide insights into how these constructs influence each other and highlight significant pathways in the studied model.

Table 4. Analysis model

Relationship	β-value	Standard deviation	*t*-value	*p*-value	Results
Direct impact					
Artificial intelligence ⟶ Academic performance (H_1)	0.097	0.041	2.329	0.021	Positive
Artificial intelligence ⟶ Mental well-being (H_2)	0.099	0.041	2.298	0.020	Positive
Climate change ⟶ Academic performance (H_3)	0.461	0.046	9.323	0.001	Positive
Climate change ⟶ Mental well-being (H4)	0.462	0.045	9.657	0.000	Positive
Artificial intelligence ⟶ Digital learning	0.085	0.040	2.094	0.038	Positive
Climate change ⟶ Digital learning	0.579	0.034	18.001	0.001	Positive
Digital learning⟶ Academic performance	0.142	0.051	2.783	0.006	Positive
Digital learning⟶ Mental well-being	0.147	0.048	2.928	0.003	Positive
Mediation impact					
Climate change⟶ Digital learning⟶ Mental well-being (H6b)	0.088	0.028	2.963	0.002	Positive
Climate change⟶ Digital learning⟶Academic performance (H6a)	0.085	0.031	2.715	0.008	Positive

Artificial intelligence⟶ Digital learning⟶ Mental well-being (H5b)	0.135	0.048	2.757	0.031	Positive
Artificial intelligence⟶ Digital learning⟶Academic performance (H5a)	0.095	0.041	2.329	0.021	Positive

It is essential to be aware that there are disadvantages to using the R2 value as the only evaluation metric (Shahzad et al, 2024). The R2 values in our model are 0.317 for mental health, 0.313 for academic achievement, and 0.337 for smart learning. As a result, the Q2 metric, which has higher prognostic value and validity, becomes the analytical focus (Sarstedt et al, 2022). High predictive relevance is indicated by a Q2 value greater than zero. Students' confidence in our model's strong predictive ability to enhance both academic achievement and mental health is demonstrated by its Q2 of 0.495. Typical f2 values of 0.03, 0.21, and 0.493 indicate modest, medium, and large effects, respectively, in accordance with standards. According to our analysis, our study's effect sizes fall between moderate and substantial (Ali et al, 2023).

The findings support students' perceptions that AI improves academic achievement (Smart et al, 2021). Scholarly interest in AI's revolutionary potential has grown, especially in the field of education (Ouyang et al, 2020). The research supports earlier findings (Zacharis, 2016), showing how AI may personalize curriculum, improve learning experiences, and raise academic achievement. The education sector now has unmatched access to AI technologies such as machine learning, which can evaluate large datasets and provide actionable insights to improve student performance (Andr´e et al, 2018; Salas-Pilco & Yang, 2022). The existing body of research confirming the advantages of emerging technologies in education is consistent (Yu & Guo, 2022). Secondly, the research shows that students think AI can have a good impact on mental health as well. The research highlights AI's potential to improve mental health support systems (Embarak, 2022), despite earlier studies highlighting possible hazards (Santovena-Casal, 2019). Artificial intelligence (AI)-powered chatbots and virtual assistants make critical information and instant assistance more accessible, democratizing

The current study contends that human oversight and ethical frameworks are essential for AI to remain a positive force (Ouyang, 2022). Previous studies on the effects of AI on mental health support these findings (Fassott, 2010). Thirdly, results show that students think climate change can improve academic achievement overall. Although the invasiveness of climate change has sparked worries, our research confirms that it can be a useful instrument for information exchange and group learning (Santovena-Casal, 2019). Furthermore, networking with professionals, experts, and mentors is made easier by climate change, which enhances academic and personal growth (Hair et al, 2013). The current research supports previous findings, indicating that time management and self-discipline are crucial for maximizing the academic potential of climate change.

Finally, the study discovered that digital learning also acts as a mediator in students' perceptions of the relationship between climate change and the twin outcomes of mental health and academic achievement. Students' broad adoption of climate change improves their academic and emotional well-being.

CONCLUSION

Important new information is revealed by examining the connections between Artificial Intelligence (AI), Academic Performance (AP), Digital Learning (DL), Climate Change (CM), and Mental Well-Being (MWB). The findings demonstrate that both AI and climate change have a major direct effect on academic performance and mental health. AI benefits digital learning in particular, which enhances academic performance and mental wellness. These results demonstrate how essential it is to address climate change-related challenges and integrate AI tools into educational settings in order to foster effective learning environments and improve students' well-being. All things considered, this study highlights how crucial it is that lawmakers and educators address these ideas holistically, supporting strategies that maximize technology while minimizing adverse environmental effects. Enhancing digital learning opportunities can have a big impact on students' mental health in addition to their academic performance, which will ultimately make them more resilient and successful.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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