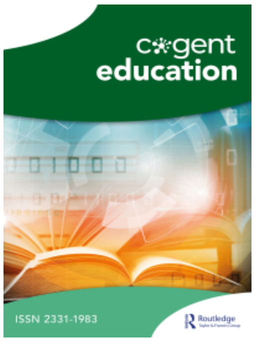

Cogent Education

ISSN: 2331-186X (Online) Journal homepage: www.tandfonline.com/journals/oaed20

Modelling the influence of antecedents of artificial intelligence on academic productivity in higher education: a mixed method approach

Moses Segbenya, Felix Senyametor, Simon-Peter Kafui Aheto, Edmond Kwesi Agormedah, Kwame Nkrumah & Rebecca Kaedebi-Donkor

To cite this article: Moses Segbenya, Felix Senyametor, Simon-Peter Kafui Aheto, Edmond Kwesi Agormedah, Kwame Nkrumah & Rebecca Kaedebi-Donkor (2024) Modelling the influence of antecedents of artificial intelligence on academic productivity in higher education: a mixed method approach, Cogent Education, 11:1, 2387943, DOI: 10.1080/2331186X.2024.2387943

To link to this article: https://doi.org/10.1080/2331186X.2024.2387943

Published online: 08 Aug 2024.

COGENT EDUCATION
2024, VOL. 11, NO. 1, 2387943
https://doi.org/10.1080/2331186X.2024.2387943

HIGHER EDUCATION | RESEARCH ARTICLE

OPEN ACCESS Check for updates

Modelling the influence of antecedents of artificial intelligence on academic productivity in higher education: a mixed method approach

Moses Segbenya[a], Felix Senyametor[b], Simon-Peter Kafui Aheto[c], Edmond Kwesi Agormedah[d], Kwame Nkrumah[e] and Rebecca Kaedebi-Donkor[f]

[a]Department of Business Programmes, College of Distance Education, University of Cape Coast, Cape Coast, Ghana; [b]Department of Education and Psychology, University of Cape Coast, Cape Coast, Ghana; [c]Department of Distance Education, School of Continuing & Distance Education, University of Ghana, Legon, Accra, Ghana; [d]Department of Business & Social Sciences Education, Faculty of Humanities and Social Sciences Education, University of Cape Coast, Cape Coast, Ghana; [e]Department of Education, College of Distance Education, University of Cape Coast, Cape Coast, Ghana; [f]Department of Education and Psychology, Faculty of Educational Foundations, University of Cape Coast, Cape Coast, Ghana

ABSTRACT

This study examined the effect of antecedents of artificial intelligence (AI) on the productivity of academics in higher education. The study was guided by the pragmatic epistemic perspective predicated on the concurrent integrated mixed-method design used with the support of a Google softcopy version of the semi-structured questionnaire (closed and open-ended questions) to collect data from 663 academics from higher educational institutions in Ghana, Nigeria, South Africa, Mexico, Germany, India, and Uganda. The quantitative data were analysed with descriptive and inferential statistical tools while thematic pattern matching was engaged to analyse the qualitative data. The study found that academics hardly use the main AI tools/platforms, and those mainly used for research and teaching-related activities were ChatGPT, OpenAI, and Quillbot. These AI tools were used mostly for general searches for information on course-related concepts, course materials, and plagiarism checks among others. The study further revealed that challenges associated with AI usage influenced the productivity of academics significantly. Finally, the availability of AI tools was found to engender AI usage but does not directly translate into the productivity of academics. The study, therefore, recommended that the management of higher educational institutions espouse policies, and provide timely information and training on the use of AI in higher education. The policies, information, and training provided should specifically address how to adopt different AI tools for specific aspects of teaching tailored and gravitated toward catalysing the productivity of academics.

ARTICLE HISTORY
Received 9 June 2024
Revised 27 July 2024
Accepted 31 July 2024

KEYWORDS
Artificial intelligence; academics; higher education; productivity; socio-technical theory; research; teaching; extension services

SUBJECTS
Higher Education; Education Policy & Politics; Educational Psychology

Introduction

The ability of scientific devices and computer systems to perform tasks that typically require human intelligence is known as artificial intelligence (AI). AI uses complex mathematical models and algorithms to analyse vast amounts of data, identify patterns, and enable machines to learn and grow over time (Osman et al., 2024; Thomas et al., 2024**).** AI also presents an immense potential to bring massive benefits to different categories of people across the globe, particularly, academics and non-academics in low, middle-income, and developed countries (LMIDCs) (Mauro et al., 2024; Hashmi & Bal, 2024). Meanwhile, AI in academia is often engulfed with myths and concerns about its ability to replace lecturers or precipitate staff redundancies (Bond et al., 2024; Jadagu, 2023). Jadagu (2023) posited that about 40% of occupations globally will be impacted by AI in terms of either enhancing it or replacing it. This required

CONTACT Moses Segbenya moses.segbenya@ucc.edu.gh Department of Business Programmes, College of Distance Education, University of Cape Coast, Cape Coast, Ghana.

policy balance to realize the full potential of AI. Therefore, AI can exacerbate already existing inequalities and create new ones for the populations, especially, by concentrating technology decision-making power only in the hands of the more dominant and powerful actors (Georgieva, 2024; Jafari & Keykha, 2023). It is crucial to remember that AI is not meant to replace teachers; rather, it is meant to enhance and augment their abilities by automating repetitive tasks and providing real-time data analysis. This allows educators to concentrate on their areas of expertise, which include research, guidance, emotional support, and inspiring creativity and critical thinking in their students (Osman et al., 2024; Thomas et al., 2024).

Because of AI's immense potential and appeal to a global audience, research interest in the field has increased. For instance, Coffey (2023) conducted a study and used a sample of 2,851 university leaders from 11 different countries (Australia, Brazil, Mexico, the Philippines, Saudi Arabia, Singapore, South Africa, Spain, the United Arab Emirates, the U.K., and the U.S.). Among other things, they found that AI helped academics to generate ideas and revolutionize teaching-learning processes. The study further found that administrators and professors used AI sporadically. Only 3% of them said they used it often, while 23% said they only used it once a month. According to the study, in contrast to Singapore (49%) and the United Arab Emirates (54%) half of college educators claimed they were frequent users. Although academics believe AI can be useful for increasing student engagement, over 30% of American educators believe AI is unethical and shouldn't be used for teaching in higher education.

In a related study on the dividends of AI, Tambuskar (2022) found that AI facilitates personalised learning experiences for learners by tailoring educational resources to individual tastes and subject-specific demands, instrumental in supporting both educators and learners via various aspects of assessment, grading, and supporting instruction. Therefore, leveraging AI is a smart game changer for the radical revolutionisation of teaching and learning across the global educational landscape (Alhussein, 2022; Chiancone, 2023; Kumar et al., 2024). Academics in higher education are the core employees around whom all academic activities revolve and academics are responsible for three main activities or mandates such as teaching, research, and extension or community engagement. The productivity of academics therefore relates to their ability to attain targets set for them by their academic institutions in the three areas of their mandates and within a stipulated time. Thus, the use of AI could provide information and other timely support to enhance the delivery of these mandates of academics (Leal Filho et al., 2024; Rahiman & Kodikal, 2024).

AI usage despite its enormous benefits, no doubt poses some specific challenges in academic institutions that relate to the integration of AI models in foreign language education, such as the lack of full integration in universities, concerns about potential distractions for students, and insufficiency of proficiently trained personnel to effectively incorporate AI into language teaching. Other challenges with AI include the security of AI algorithms, developing a research strategy for responsible AI implementation in universities, and the need for a solid governance system. Others include the challenge of planning, designing, and implementing digital skills and a universal digital language supported by AI formats to meet the demands of the information society (Hazaimeh & Al-Ansi, 2024; Rawas, 2024). It is also important to note that barriers and challenges that hinder the adoption of artificial intelligence among students and academics related to teaching include limited language options, academic dishonesty, biases and lack of accountability, laziness among students and lecturers, and lack of data infrastructure (Hazaimeh & Al-Ansi, 2024; Saaida, 2023). Meanwhile, the effect of antecedents of artificial intelligence on the productivity of academics in higher education can be considered in relation to how generative artificial intelligence technologies shape partial job displacement and labor productivity and growth (Dabija & Vătămănescu, 2023; Lazaroiu & Rogalska, 2023; Peters et al., 2023).

Existing studies have confirmed AI adoption and usage in higher educational institutions across the globe (Baidoo-Anu & Ansah, 2023; Caffey et al., 2023; Hazaimeh & Al-Ansi, 2024; Miao et al., 2023; Yildiz, 2023). These studies focused on the levels of associated benefits with AI usage (Kuleto et al., 2021) whiles others focused on challenges of AI usage (Al Husseiny, 2023; Chaka, 2022; Hazaimeh & Al-Ansi, 2024; Hutson et al., 2022; Jafari & Keykha, 2023; McGrath et al., 2023; Ocaña-Fernández et al., 2019; Segbenya et al., 2023). Most of the existing studies have focused on postgraduate students and academics in the universities without considering other tertiary institutions in the subsector such as colleges of education and other technical universities. Existing studies on AI adoption and usage in higher education also failed to examine the extent to which AI adoption and usage and its associated benefits and challenges significantly influence productivity among academics in higher education creating a conceptual gap to be filled. Thus, there is a dearth of research on the effect of AI on productivity among academics in higher education. Meanwhile, in the era of AI usage for work schedules in several other sectors such as health, engineering, and others, there is the need to interrogate the AI platforms available for academic activities, and how their benefits and challenges relate to the productivity of academics in higher education subsector. It is for this purpose that this study models the effect of antecedents of AI (such as AI tools/platforms availability, AI usage, benefits, and challenges) on the productivity of academics in higher education. This study considers academics from three main institutions in the higher education landscape- Colleges of Education, Technical Universities, and Academic Universities across the globe.

The three objectives that guided the study were to:

1. examine how and what kind of AI platforms or tools are most frequently employed by academics in higher education.
2. Assess the degree to which academics in higher education see the advantages and difficulties related to AI platforms.
3. Assess the effects of AI on higher education faculty productivity.

The results of this study will further our understanding of how technology affects academic institutions' human resource and work performance. The literature review, methods, results and conclusions, discussions of the results, policy and practical implications, conclusion, recommendations, and suggestions for additional research are covered in the remaining sections of the study.

Literature review

Theoretical review

The Socio-Technical Systems theory, developed by Molleman and Broekhuis (2001), served as the theoretical foundation for this investigation (Segbenya et al., 2023). To describe their possible impact on the use of technology in teaching and learning, two interdependent subsystems known as the social and technological systems are integrated into a socio-technical system. The theory contends that both technological and social components have an impact on how technology is adopted (Segbenya et al., 2023). The social subsystem of the theory could be associated with the diversity found in the educational environment, which is a part of every nation's social structure (Segbenya et al., 2023). Technology is being used in teaching and research as a result of developments and technological improvements (Aheto et al., 2024). In the realm of higher learning technology, the development and use of AI constitute a noteworthy advancement (Aheto et al., 2024). The use of AI by academics and faculty members in higher education has the potential to impact interactions, values, beliefs, and productivity in terms of research output and teaching outcomes, as well as the cultural environment and human connections that exist in higher education prior to the arrival of AI technology/platform (Segbenya et al., 2023). As such, academics may face significant difficulties when utilizing AI. Academic researchers apply the second axiom, which refers to the technical subsystem, to the use of AI for academic activities. This includes the use of technological resources, technical assistance systems, and expertise (Molleman & Broekhuis, 2001). Because academics in higher education are socially and technically related, the aforementioned explanation further supports the application of the socio-technical theory in this study.

Conceptual review and hypotheses development

This section discusses the relationships between the various components of the study and the specific gaps that the specific hypothesis addresses in the study.

Challenges with AI and productivity among academics

Academics in higher educational institutions remain as the core employees around whom the academic activities revolve (Segbenya et al., 2021). All other employees apart from academics only provide a supporting role for achievement of the institutional goals. Academics' productivity relates to three main activities such as teaching, research, and extension or community engagement (McGrath et al., 2023). Thus, productivity among academics in higher education is measured by how far each academic can meet targets set in the three main areas within a specific time frame in their respective institutions (Segbenya et al., 2021, McGrath et al., 2023). The performance of the three academic activities (research, teaching, and extension services) largely depends on information. One major tool or platform for accessing a volume of relevant information that can aid teaching and learning as well as research and extension activities is technology, specifically artificial intelligence (Aheto et al., 2024; Anapey & Aheto, 2022). Other studies (Al Husseiny, 2023; Chaka, 2022; Hutson et al., 2022; Jafari & Keykha, 2023; McGrath et al., 2023) have again confirmed that the use of AI for research and teaching-related activities among academics is not without challenges. These challenges could include lack of institutional policy, reliability and validity of outputs, and effect on creativity, leadership, and teamwork (Segbenya et al., 2023). Other challenges could also come in the form of a lack of institutional support in terms of resources and a lack of skills to navigate the AI platforms (Hutson et al., 2022). Existing studies (Al Husseiny, 2023; Chaka, 2022; Hutson et al., 2022; Jafari & Keykha, 2023; McGrath et al., 2023) only appear to investigate challenges associated with AI among lecturers in university and postgraduate students without addressing the larger tertiary subsector that includes colleges of education and technical universities. To fill this void in the existing literature, this study conjectured that:

H1. Challenges associated with AI will significantly influence the productivity of academics in higher education.

Availability of AI tools/platforms and productivity among academics in higher education

The accessibility of AI platforms or tools by academics for research, teaching, and extension activities will largely depend on the kind of AI tools available (Baidoo-Anu & Ansah, 2023; Yildiz, 2023). Availability in this sense is explained as the AI tool/platforms that academics are aware of and are conversant in using for their academic activities (Baidoo-Anu & Ansah, 2023; Miao et al., 2023; Yildiz, 2023). That means academics will need information not only on the availability of AI tools but also on what their uses are. This is because academics do several activities within their three main mandates of teaching, research, and extension services (Segbenya et al., 2022). In the area of teaching, AI platforms could help in searching for information on concepts to be taught, preparing course outlines, and power points, and writing commands, among others. In terms of research, academics can use AI to help in searching for literature, preparing end-of-text references, and information for writing the literature review among others (Segbenya et al., 2023). The effectiveness of how academics discharge all three core mandates determines whether the academics are productive or not. Thus, if a faculty member or an academic is unable to meet the target set for him/her for a specific period, then such an academic is deemed unproductive. Some AI platforms available that academics can leverage to enhance their productivity in higher education are PyTorch, RasaAI, AmazonSageMaker, TypingMind, Google Cloud Platform, ChatGPT, OpenAI, and Quillbot (Segbenya et al., 2023). Existing studies appear to have only examined the AI tools available to postgraduate students without considering academics or faculty members, and artificial intelligence applications in higher education (Miao et al., 2023; Salas-Pilco & Yang, 2022; Segbenya et al., 2023). Against the backdrop of plugging this void in research, this study conjectured that:

H2. The availability of artificial intelligence tools/platforms (AIT) will significantly influence productivity of academics in higher education.

Availability of artificial intelligence platforms/tools and usage of AI among academics

It is not enough for academics to just be aware of which AI platforms exist but knowledge and competence to use these AI tools could be a potent reinforcement for AI usage among academics

(Chan & Hu, 2023). Lack of the necessary skills to navigate these AI platforms could also become a demotivating factor for academics' avoidance of AI platforms despite the benefits associated with their engagement in academic activities (Yildiz, 2023). It is also possible that the usage of AI among academics could also differ in terms of levels where there could be high, moderate, or low usage of AI for academic activities among academics. Existing studies by Segbenya et al. (2023) among others seem to only touch on AI usage among postgraduate students, and the main challenges of artificial intelligence in the university without reference to the level of usage among academics in higher education. In light of filling this gap in the literature, this study conjectured that:

H3. The availability of artificial intelligence tools/platforms (AIT) will significantly influence the usage of artificial intelligence (AIU) of academics in higher education,

AI usage, productivity among academics, and challenges associated with AI usage

For the continued use of AI in academia to be successful, productivity in academia must be increased. It will be challenging to persuade academics to stick with using AI platforms for their academic activities if their use doesn't increase productivity in the areas of research, teaching, and extension services. Research has demonstrated the application of AI in higher education as well as the effects of artificial intelligence on it (Chan & Hu, 2023; Crompton & Burke, 2023; Rasul et al., 2023; Salas-Pilco & Yang, 2022; Schiller International University [SIU], 2023; Segbenya et al., 2023). However, existing studies did not focus on how the usage of AI could translate into the productivity of academics in higher education. As much as the usage of AI platforms among academics could engender high productivity of academics, it is equally important to emphasize that the level of the usage could also determine the level of challenges that academics could be facing with the use of AI for their academic activities (Segbenya et al., 2023). Existing studies again appear not to have investigated inherent challenges with AI usage among academics. To fill this void in the literature, the study conjectured that:

H4. The use of AI (AIU) will have an impact on academic output in higher education.

H5. The usage of AI in higher education (AIU) will be greatly impacted by challenges with AI (AIU).

Based on the conceptual and theoretical reviews, a conceptual framework was carved to guide the study as presented in Figure 1.

Methodology

The pragmatic epistemic perspective—which combines positivist and interpretivist methodologies—was used for this investigation (Segbenya et al., 2019; 2023). Specifically, the concurrent integrated mixed technique was applied. In this study, the qualitative methodology was used as an adjunct to the quantitative method as part of an ongoing integrated mixed-method investigation. The sample for this study consisted of 663 academics at different ranks (Professors, Senior/Principal/Chief Lecturers, and Lecturers)

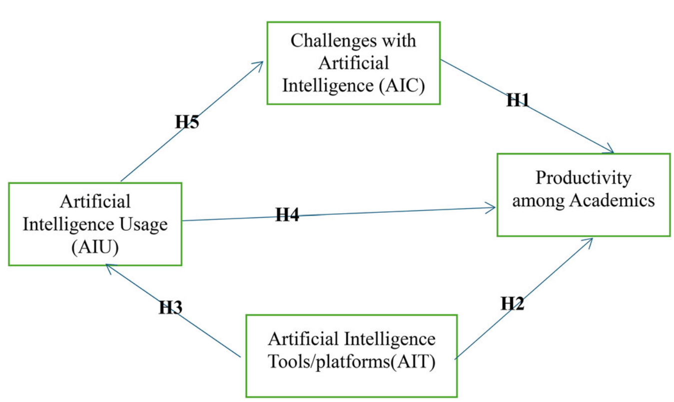

Figure 1. Conceptual framework of the study.

from public and private technical and academic universities as well as colleges of education, worldwide. Stratified sampling was used to ensure that all academics or faculty members' strata, including gender, country, and area of specialization, were represented in the study population.

Due to the mixed methods methodology employed, both closed- and open-ended items were included in the study's questionnaire, enabling the simultaneous collection of respondents' qualitative and quantitative data. The questionnaire was divided into two parts. Part One examined the demographics of the respondents, while Part Two included the study's objectives and hypotheses. The questionnaire was scored using a Likert scale, where 1 meant strongly disagree, 2 disagree, 3 agree, and 4 strongly agree (Donkor & Segbenya, 2023; Oppong & Segbenya, 2023; Segbenya & Okorley, 2022). This study did not allow for ambiguous or indifferent answers because each participant had to indicate whether or not they agreed with the items/questions. Because of this, a four-point rating scale was employed rather than the traditional five. The four-point scale was used for assessment rather than the five-point Likert scale because neutral responses and the results they were associated with did not fall into either of the two extremes (agree or disagree). This is because the neutral or undecided response could also have an impact on the mean values or conclusions. All of the data regarding the applications, advantages, and difficulties of AI platforms and tools came from Chan and Hu (2023) and Segbenya et al. (2023).

The instrument's validity and reliability were evaluated in a pilot test, and since the test's Cronbach Alpha value was higher than the minimum criterion of 0.70, the instrument was considered suitable for use in primary data collection. Before the instrument was administered, the opinions of experts were also employed to confirm the instrument's face validity. From January 2024 to March 2024, the primary data gathering was completed. Ethical concerns about informed consent, privacy, the option to withdraw even after the procedure had started, and anonymity were all addressed. PLS-Structural Equation Modelling was used to evaluate the data, and descriptive statistics were used to address the objectives that drove the investigation.

Results and findings

This section presents the findings of the study in two parts; (1) respondents' demographics and (2) results on the hypotheses guiding the study. The results on the demographic characteristics of respondents are presented in Table 1. From Table 1, the majority of the respondents for this study were male academics (65.4%) with education background as area of specialisation (47.4%) aged between 41 and 50 years (42.1%). The results also revealed that the majority of the respondents were teaching in academic higher institutions (50.4%) which were public institutions (96.2%). It is also clear from Table 1 that the majority of the respondents were lecturers/tutors in their academic institutions (45.1%) followed by those who were in the Senior/principal/chief lecturer/tutor category (28.6%). Most of the respondents were also coming from Ghana (78.9%) followed by Nigeria (9.0%).

Table 2 displays the results of the first part of the first objective, which focuses on the kinds of artificial intelligence platforms and technologies that lecturers in academic institutions employ. Eleven artificial intelligence tools were presented to respondents to determine which of them were not known, known but never used, and known and used. The results in Table 2 revealed that in terms of AI tools that were not known to the majority of the academics considered in this study were H20 ai (72.2%), PyTorch (71.4%), RasaAI (67.7%), AmazonSageMaker (65.4%), and TypingMind (63.9%). The majority of the respondents also revealed that they were familiar with the Google Cloud platform (39.1%) but never used it in higher education. The results in Table 2 further revealed that the AI platforms used by academics in higher education were ChatGPT (60.9%), OpenAI (39.1%), and Quillbot (38.3%)

The second section of the first objective, also looked at how academics in higher education employ AI tools and platforms. The results are based on the three main perspectives of the job description of every academic in higher education. These were research, teaching, and extension mandates of every academic in higher education. The results as presented in Table 3 revealed that in terms of research, academics in higher education used artificial intelligence for general learning ($M = 1.9549$; $SD = .71415$), paraphrasing written text ($M = 1.9173$; $SD = .79574$) and searching for literature ($M = 1.8872$; $SD = .77279$), writing introduction & and review of literature for articles ($M = 1.7669$; $SD = .75537$), and intext

Table 1. Biodata characteristics of respondents.

Biodata of characteristics	Frequency	Percent
Gender		
Male	435	65.4
Female	230	34.6
Total	665	100.0
Age		
21–30	20	3.0
31–40	185	27.8
41–50	280	42.1
51 and above	180	27.1
Total	665	100.0
Specialisation		
Business programmes	215	32.3
Education programme	315	47.4
ICT programmes	50	7.5
Science and Health	25	3.8
Agriculture	15	2.3
Others	30	4.5
Engineering	15	2.3
Total	665	100.0
Type of institution		
Academic institution	335	50.4
Technical institution	50	7.5
College of education	280	42.1
Total	665	100.0
Classification		
Public	640	96.2
Private	25	3.8
Total	665	100.0
Rank		
Professor	40	6.0
Senior/Principal/chief lecturer/ tutor	190	28.6
Lecturer/Tutor	300	45.1
Assistant Lecturer/others	135	20.3
Total	665	100.0
Country		
Ghana	525	78.9
Nigeria	60	9.0
South Africa	35	5.3
Others/Mexico/Germany/India/Uganda	45	6.8
Total	665	100.0

Source: Field data (2024).

Table 2. Artificial intelligence tools used by academics in higher education.

		NA/Not aware		ANU/Aware but Never Used		AU/Aware and used		Total	
	AI tools/platforms	No	%	No	%	No	%	No	%
1	Chartgpt	60	9.0	200	30.1	405	60.9	665	100.0
2	H20 ai	480	72.2	160	24.1	25	3.8	665	100.0
3	TypingMind	425	63.9	180	27.1	60	9.0	665	100.0
4	OpenAI	165	24.8	240	36.1	260	39.1	665	100.0
5	AmazonSageMaker	435	65.4	190	28.6	40	6.0	665	100.0
6	Chartbox	285	42.9	265	39.8	115	17.3	665	100.0
7	Google cloudplatform	235	35.3	260	39.1	170	25.6	665	100.0
8	PyTorch	475	71.4	170	25.6	20	3.0	665	100.0
9	MicrosoftBingAI	260	39.1	240	36.1	165	24.8	665	100.0
10	Quillbot	235	35.3	175	26.3	255	38.3	665	100.0
11	RasaAI	450	67.7	175	26.3	40	6.0	665	100.0

Source: Field data (2024).

and end of text citation purposes (M = 1.5263; SD = .72164). The high rating of the use of AI for these five research-related activities is further in line with the overall mean values of (M = 1.6607, SD = 0.71624) which suggests that artificial intelligence tools were highly used for research activities among academics in higher education.

The results in Table 3 also revealed that the specific teaching-related activities of the academics in higher education that artificial intelligence platforms/tools were used for were searching for information on course-related concepts (M = 1.8421; SD= .78428), searching for course materials (M = 1.9323; SD = .78766), subjecting written text of students to plagiarism checks (M = 1.6617; SD= .81299), preparing

Table 3. Uses of artificial intelligence by academics in higher education.

Research-related activities	Mean	Std. Dev	Ranked
1. Just used for learning in general	1.9549	.71415	High
2. Paraphrasing written texts	1.9173	.79574	High
3. Searching for literature	1.8872	.77279	High
4. Writing introduction & and review of literature for articles	1.7669	.75537	High
5. For intext and list of references citation purposes-	1.5263	.72164	High
6. Writing grant or research proposal	1.4511	.69925	Low
7. Conducting data analysis	1.4060	.62620	Low
8. Writing commands for software	1.3759	.64470	Low
Subtotal	1.6607	0.716235	High
Teaching–related activities	**Mean**	**Std. Dev**	**Rank**
9. Searching for information on course-related concepts	1.9323	.78766	High
10. Searching for course materials	1.8421	.78428	High
11. Subjecting written text of students to plagiarism checks	1.6617	.81299	High
12. Preparing power points	1.5940	.75687	High
13. Preparing Continuous Assessment Questions	1.5038	.70095	High
14. Preparing course outline	1.5038	.73247	High
15. Preparing end-semester examination questions	1.4737	.68963	Low
Subtotal	1.6445	0.75212	High
Extension-related activities	**Mean**	**Std. Dev**	**Rank**
16. Use for finding locations	1.5714	.71858	High
17. Used for entertainment (Video games)	1.4887	.69004	Low
18. Use for response to emails	1.4586	.67787	Low
19. Used for checking your health-related challenges	1.4286	.64104	Low
20. Use for internal or external transportation arrangements (booking and ticketing)	1.3910	.62376	Low
21. Used for security and protection (detect threat, fraud detection, risk assessment)	1.3383	.59979	Low
Subtotal	1.4461	0.6585	Low
Overall total	1.5009	0.71171	High

Note: $N = 665$, Minimum = 1, Maximum = 3, 1.00–1.49 = low, 1.5–1.9 = high and 2.0 and above = very high.
Source: Field data (2024).

power points (M = 1.5940; SD = .75687), and continuous assessment questions (M = 1.5038; SD=.70095). The high level of the use of artificial intelligence tools for these teaching activities further confirms the high rating of the overall mean value for the teaching variable (M = 1.6445; SD = 0.75212)

The last component of academics' job descriptio in higher education was extension services or community engagement and the results of how artificial intelligence is used for such engagement are also presented in Table 3. The results revealed that apart from using artificial intelligence tools for finding locations (M = 1.5714; SD=.71858), all the items used to measure the extension or community engagement variables were rated low which further translated into the low rating of the extension service variable with an overall mean value of (M = 1.4461; SD= 0.65851). The results mean that artificial intelligence tools were hardly used by academics for extension services or other uses.

Figure 2 presents the summary of the results of the uses of artificial intelligence tools among academics. The results show that the use of artificial intelligence in higher education was higher for research activities with a mean value of (M = 1.6607) followed by teaching activities (M = 1.6445). The rating for these two components of the academic work schedules was higher than the overall mean average value of (M = 1.5009). Extension service was rated lower (M = 1.4461) as compared to other aspects of the academics job (research and teaching) and the overall mean average value.

Objective two: Evaluating the level of perceived benefits, and challenges associated with AI platforms used by academics in higher education

Table 4 presents the findings for objective two, which focused on the advantages and difficulties of using AI among academics in educational institutions. According to the results, using artificial intelligence (AI) for analyzing data in conducting research (M = 2.7218; SD = 1.00715), teaching academic courses (M = 2.6391; SD = .96113), enhancing the curriculum (M = 2.5940; SD = .98205), and gaining insight into research work (M = 2.5865; SD= 1.01293) are the top seven benefits of AI to academics in higher education. The rest were improvements in the accuracy and efficiency of research findings (M = 2.5714; SD = 1.04338), and speed of data processing (M = 2.5564; SD = 1.02244). That notwithstanding, the overall mean value of M = 2.4552; SD= 1.0191 suggests that the general rating for benefits derived from using AI among academics in higher education was low.

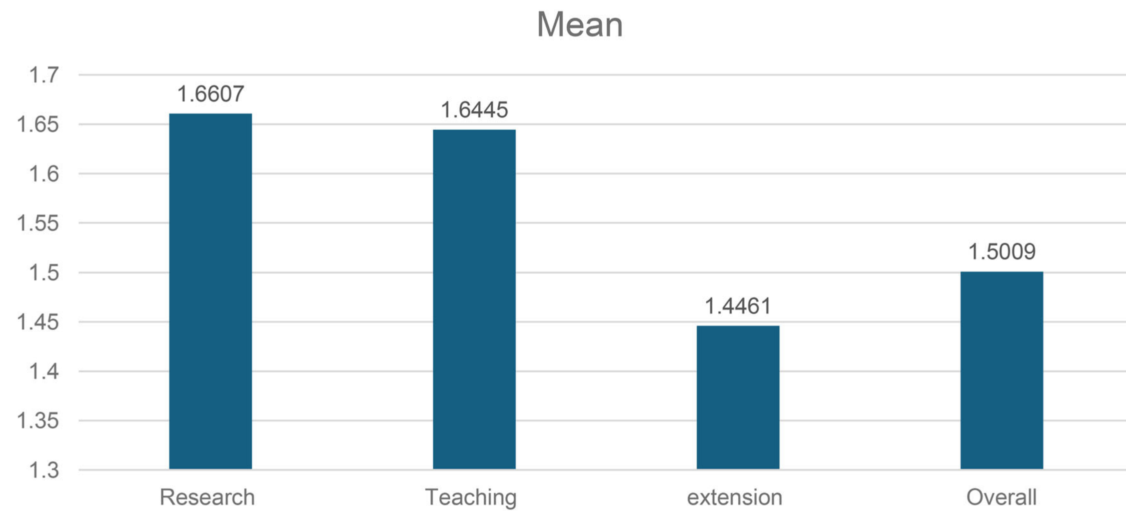

Figure 2. AI usage among academics in higher education.

Table 4. Benefits and challenges associated with the use of AI by academics in higher education.

Benefits	Mean	Std. Dev	Rank
1. AI tools are essential for data analysis in my research activities	2.7218	1.00715	High
2. AI tools are essential for enhancing teaching in my academic courses	2.6391	.96113	High
3. I feel comfortable using AI tools to improve educational content	2.5940	.98205	High
4. AI has enhanced the quality of insights and findings in my research	2.5865	1.01293	High
5. AI has improved the efficiency and accuracy of my research work	2.5714	1.04338	High
6. Using AI tools has increased the speed of data processing in my research	2.5564	1.02244	High
7. AI tools are essential for enhancing teaching in my academic activities	2.5533	1.05668	High
8. I feel confident in using AI algorithms and techniques for my research	2.4887	1.01655	Low
9. AI has improved the effectiveness and interactivity of my teaching methods	2.4812	.97098	Low
10. The use of AI tools has increased student engagement and participation in my classes	2.3684	1.04473	Low
11. AI has improved the personalization of learning in my classes.	2.3340	1.02434	Low
12. I have received adequate training and support to effectively use AI tools in my research or teaching	2.0376	1.07970	Low
13. I have received adequate training to use AI tools in my teaching activities.	1.9850	1.02664	Low
Overall mean	2.4552	1.0191	Low
Challenges	Mean	Std. Dev	
14. My institution is yet to provide support (financial, data, internet etc) for the AI tool I used for research and teaching. (Resources)	2.7368	1.05493	High
15. My institution has yet to provide training for academics on how to use AI for teaching and research (Training).	2.6842	1.10699	High
16. The artificial intelligence (AI) program I utilized for my research isn't flawless and occasionally yields inaccurate or deceptive data (accuracy and reliability)	2.5639	1.03663	High
17. There isn't a defined policy on the use of AI in research and teaching at my university (Policy)	2.5489	1.16724	High
18. Reliance too much on the AI program I utilized for my schoolwork can impair my ability to think critically and solve problems, as well as my desire to interact with people in a proactive manner (Dependence).	2.5188	1.08106	High
19. The machine-learning model of the AI software I employed for my academic work was trained on potentially biased data. This may lead to biased outputs and the maintenance of negative stereotypes. (Bias).	2.3459	1.11158	Low
Overall mean	2.566	1.0931	High

Note: $N = 665$, Minimum = 1, Maximum = 4, Scale: 1.5–1.9 = very low, 2.0–2.4 low, 2.5–2.9 = high and 3.0 and above = very high.
Source: Field survey (2024).

Results for the challenges associated with the use of AI by academics in higher education as presented in Table 4 also revealed that academics had several challenges with the use of AI in higher education. These challenges were lack/inadequate institutional support (financial, data, internet etc) for AI platforms used ($M = 2.7368$; $SD = 1.05493$), lack of training for the use of AI in higher education ($M = 2.6842$; $SD = 1.10699$), accuracy and reliability of some content produced by AI ($M = 2.5639$; $SD = 1.03663$) and lack of clear institutional policy on the use of AI in higher education ($M = 2.5489$; $SD = 1.16724$). Another notable challenge faced by faculty members or academics in higher education was the loss of creativity and problem-solving skills due to overdependence on AI for academic work ($M = 2.5188$; $SD = 1.08106$).

Table 5. Solutions to addressing challenges associated with AI usage among academics in higher education.

Challenges	ID sample quotes or from respondents
1. Resources	1. 'Making resource materials readily available for researchers'
	2. 'Procure AI software for the use of academic activities'
	3. 'By providing the financial and moral support'
2. Training	1. 'Organising frequent workshops on its positive and negative effects'
	2. 'Providing more training'
	3. 'Education and orientation on the use of AI'
3. Policy	1. 'A clear AI policy for staff and students'
	2. 'Use of code of ethics/strict rules on how to use'
	3. 'Place emphasis on plagiarism checks by making it compulsory'
	4. 'Policy on the use of Turnitin to check similarity index'
4. Accuracy and reliability	1. 'Use the advanced version of AI software to reduce the level of errors'
5. Overdependency/academic dishonesty/ loss of creativity and problem-solving skills	1. 'Effective supervision'
	2. 'Ask questions that require critical thinking and application, diversify assignments, etc'

Source: Field survey (2024).

In addition, the respondents were asked to recommend strategies for resolving issues related to the application of AI in higher education. Table 5 displays the findings from the qualitative data collected through open-ended questionnaire items. According to the findings, there is lack of institutional support for using AI in higher education through the supply of resources and training on the advantages and disadvantages of this approach. The necessity for a clear policy on the use of AI by professors and students in higher education was also mentioned by respondents. Lastly, academics also made suggestions for structuring academic curricula and forms of assessment to reduce over-dependency on AI and its subsequent effect on creativity and problem-solving skills among its users.

Testing for the hypotheses guiding the study

The second part of the results of this study presents an inferential analysis to test the hypotheses guiding the study. The testing of the hypotheses was preceded by three preliminary analyses. Meanwhile, before the preliminary analysis, the study checked the item loadings for each variable, and items that loaded below the minimum criteria of 07.70 according to Segbenya and Anokye (2023) were deleted and the acceptable items with their respective variables were presented in Figure 3.

Table 6 displays the findings of the initial preliminary study that was carried out utilizing the construct validity and reliability of the PLS-SEM model. The construct reliability and validity were assessed using four primary indicators, rho_A, Composite Reliability, Cronbach's Alpha, and Average Variance Extracted (AVE). For the study, a minimum threshold of 0.70 was determined to be acceptable for a variable for the first three indications. The threshold for the last indicator was also 0.50 for the inclusion of an item/variable in the study. The results show that all the values obtained under the first three indicators ranged between 0.801 and 0.956 which were above the minimum threshold of 0.70. The AVE values obtained also ranged between 0.577 and 0.714 and were also above the 0.50 threshold (Segbenya & Minadzi, 2023). Thus, it can be concluded that the PLS-SEM used for this study passed the construct reliability and validity test.

Note: Significance for values in Table 6 are 0.70 and above for rho_A, Composite Reliability, Cronbach's Alpha, and 0.50 and above for Average Variance Extracted (AVE).

The Heterotrait-Monotrait Ratio (HTMT), based on Hair et al. (2017), Donkor and Segbenya (2023), and Yahaya and Segbenya (2023) recommendations of a maximum threshold of 0.850, and the Fornell-Larcker Criterion were the two indices used to achieve this in the second initial analysis. The results are shown in Table 7. The data indicates that all of the variables pass the discriminant validity test as the Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) scores were all below the maximum threshold of 0.850. According to Segbenya and Minadzi (2023) recommendation, the most recent exploratory analysis aimed to ascertain whether multicollinearity existed. The threshold of 3.30 was employed to ascertain the acceptance of variables. According to the study's results, every value in Table 6 was below the 3.30 minimum threshold, indicating that multi-collinearity was not present and that the data may be used for additional inferential analysis.

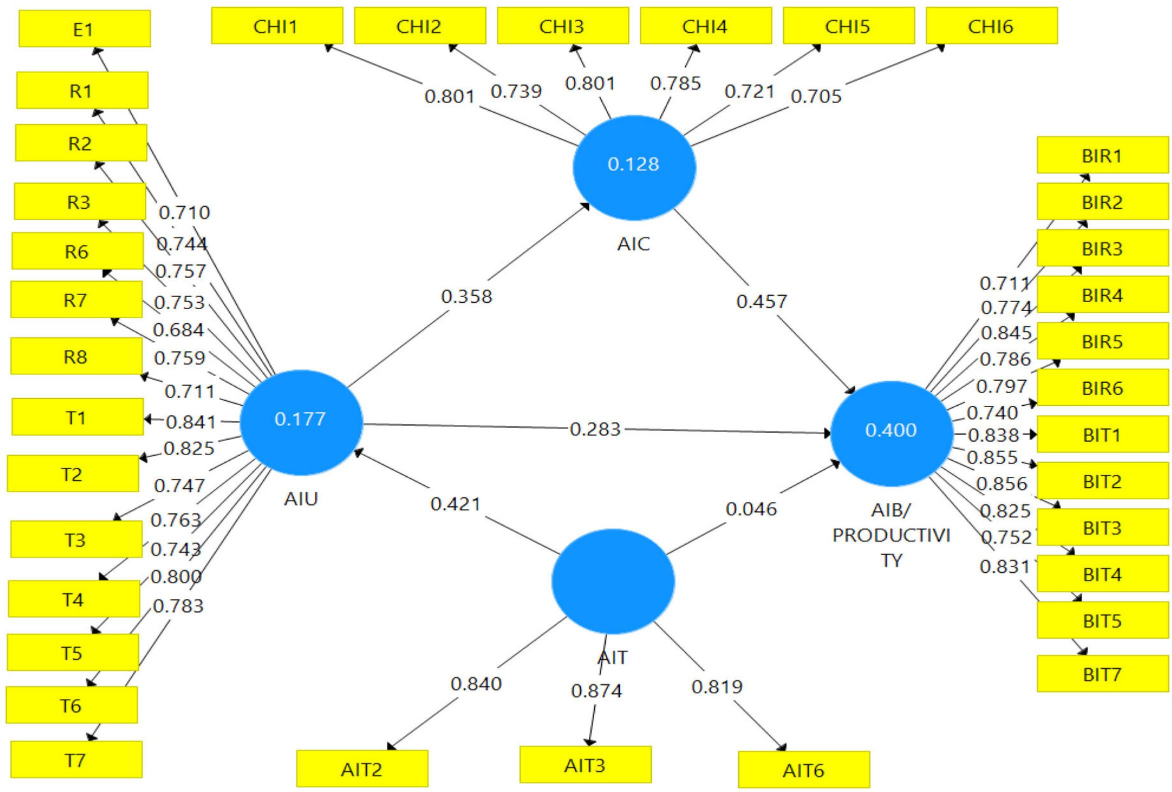

Figure 3. Algorithm of accepted items and their variables.

Table 6. Construct reliability and validity regarding the variables of the study.

	Cronbach's Alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Productivity	0.949	0.951	0.956	0.643
AIC	0.855	0.862	0.891	0.577
AIT	0.801	0.807	0.882	0.714
AIU	0.943	0.947	0.950	0.577

Source: Field survey (2024).

Table 7. Discriminant validity of the variables of the study.

Fornell-Larcker criterion	Productivity	AIC	AIT	AIU
Productivity	0.802			
AIC	0.564	0.760		
AIT	0.218	0.114	0.845	
AIU	0.467	0.358	0.421	0.760
Heterotrait-Monotrait ratio (HTMT)	**Productivity**	**AIC**	**AIT**	**AIU**
Productivity				
AIC	0.613			
AIT	0.242	0.210		
AIU	0.480	0.371	0.479	
Inner VIF values	**Productivity**	**AIC**	**AIT**	**AIU**
Productivity				
AIC	1.149			
AIT	1.217			1.000
AIU	1.378	1.000		

Source: Field survey (2024).
Note: Significance for values in Table 7 is values below 0.850.

The results of the main path analysis done to test the five hypotheses of the study are presented in Table 8. The results revealed that out of the five hypotheses, four hypotheses were accepted because they attained a statistical significance level and a hypothesis was rejected because it had a non-significant relationship. Specifically, hypothesis one was supported because AI challenges in higher education

Table 8. Path coefficients for establishing relationship between variables of the study.

	Original sample	Sample mean	Standard Deviation	*T* statistics	P values	Confidence Intervals 2.5%	Confidence Intervals 97.5%
1. AIC -> Productivity	0.457	0.463	0.087	5.253	0.000	0.283	0.624
2. AIT -> Productivity	0.046	0.052	0.081	0.574	0.566	0.113	0.216
3. AIT -> AIU	0.421	0.422	0.083	5.058	0.000	0.255	0.573
4. AIU -> Productivity	0.283	0.283	0.086	3.303	0.001	0.111	0.446
5. AIU -> AIC	0.358	0.363	0.073	4.924	0.000	0.219	0.484

R square	*R* square	*R* square adjusted
Productivity	0.400	0.386
AIC	0.128	0.122
AIU	0.177	0.171

f Square	Productivity	AIC	AIT	AIU
Productivity				
AIC	0.303			
AIT	0.003			0.215
AIU	0.097	0.147		

Source: Field survey (2024).
Note: Significance for values in Table 8 is 0.05 for the p-values established for path relations.

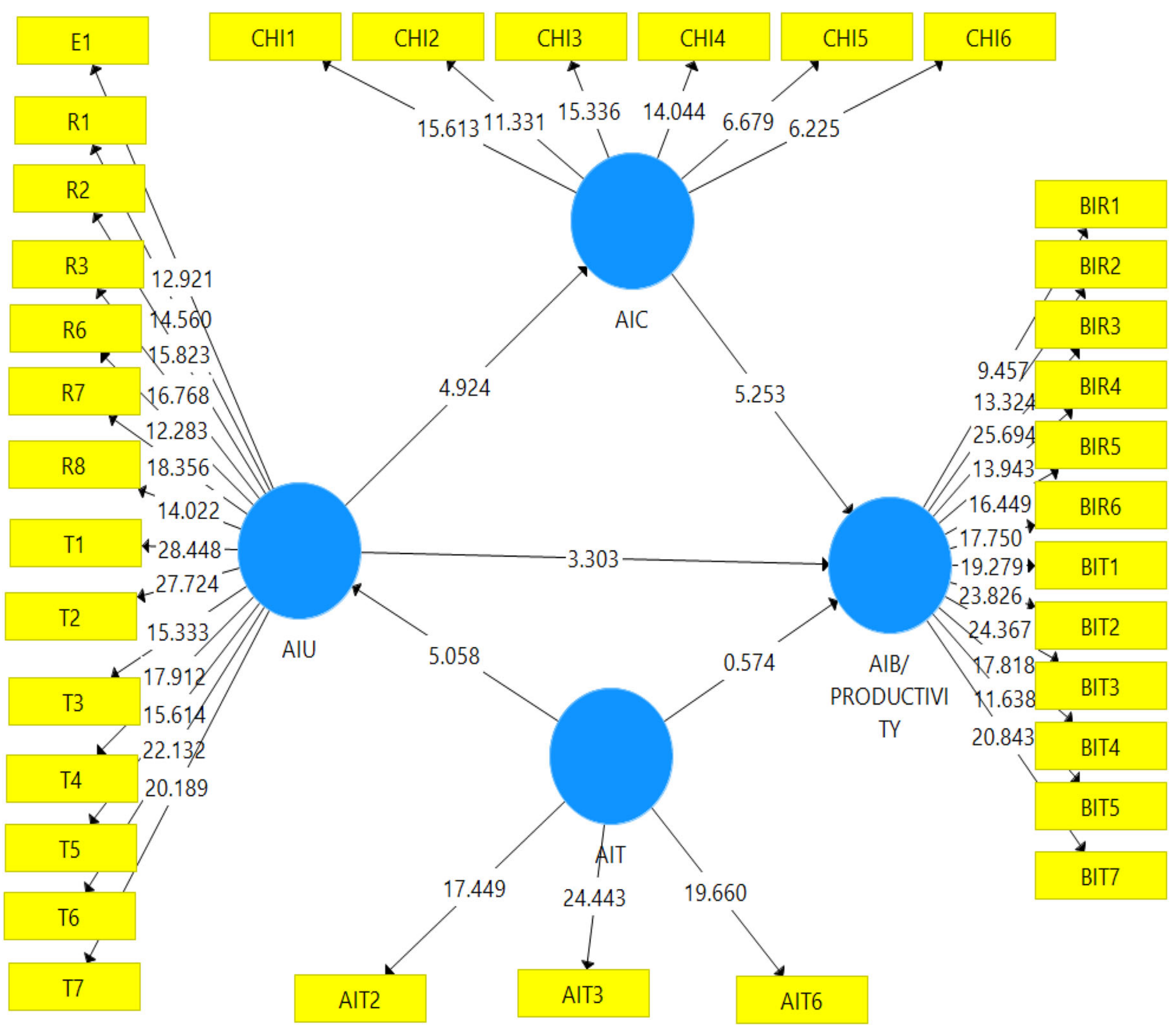

Figure 4. Bootstrapping results.

(AIC) were significantly related to the productivity of academics in higher education at ($\beta = 0.457$, $t = 5.253$, $p < 0.000$). Hypothesis two was however not supported because AI tools/platforms (AIT) had a non-significant relationship with the productivity of academics in higher education at ($\beta = 0.046$,

$t = 0.574$, $p < 0.566$). Hypothesis three was accepted since AI tools/platforms availability influenced AI usage of academics in higher education at ($\beta = 0.421$, $t = 5.058$, $p < 0.000$). The study further accepted hypotheses four and five of the study since AI usage (AIU) influenced both productivity of academics at ($\beta = 0.283$, $t = 3.303$, $p < 0.001$) for hypothesis four, and challenges associated with AI usage in higher education at ($\beta = 0.358$, $t = 4.924$, $p < 0.000$).

The overall contribution of all the variables of the study is also explained in the model as presented in Table 8. The results revealed that the PLS-SEM explained approximately 40% variance in productivity of academics in higher education. A total of 13% variance in challenges associated with AI usage among academics and finally 18% variance in AI usage among academics.

The significance and non-significance results obtained as presented in Table 8 are further supported by the pictorial presentation of the interconnectedness of the variables of the study as shown in Figure 4.

Discussion of the results

This section discusses the empirical findings of this study and how these findings relate to existing studies. The results for objective one of the study that academics in higher education that the AI tools used by academics in higher education were Chartgpt, OpenAI, and Quillbot. The purpose of using these AI platforms was for research and teaching-related activities. The results mean that academics and faculty members used artificial intelligence tools like Chartgpt, OpenAI, and Quillbot for teaching and research-related activities. The ChatGPT is a text-generating tools that help individuals to generate text on a concept. The Quillbot AI tool is also a paraphrasing tools that aid academics in their writing. The high level of usage of ChatGPT, OpenAI, and Quillbot agrees with earlier findings of Segbenya et al. (2023) that these same tools were highly used among learners. The findings mean that both postgraduate students and faculty members in academics are all using these AI tools for academic activities. As much as this study found that faculty members were using these AI tools mostly for a general search for information on course-related concepts, searching for course materials, and subjecting written text of students to plagiarism checks; the earlier study by Segbenya et al. (2023) found that postgraduates were using the same AI tools for doing literature searches, composing assignments, and learning in general.

The results for the study's second objective also revealed that several important advantages of using AI among academics and faculty members in higher education were assisting in data analysis, improving educational content, gaining insight into research work, and improving the accuracy and efficiency of research findings. This means that benefits derived from using these AI among academics could be responsible for its continued use among academics. Academics and faculty memebers as rational users of AI platforms will only continue to use these platforms if their needs and expectations for using these platforms are met. That is, although academics and faculty members could patronise these platforms for the first time, their continued usage is largely dependent on the benefits derived from them. The findings corroborate those of Chan and Hu (2023), who found that learners benefited from using AI software in terms of education, research, and information support, as well as early or on-time completion of academic duties. This means that AI usage benefits both faculty members/academics and postgraduate students in higher education.

Despite the benefits of AI to academics and faculty memebers in higher education, academics also encountered some challenges. Some of the key challenges encountered were financial challenges associated with data and internet support for AI platforms used, and lack of training for academics on the use of AI. These challenges are either within the institutions where these academics work or feed into the general national challenges that confront others apart from academics. A typical example in this case was internet connectivity and the cost of data for using the internet. Other challenges encountered were the accuracy and reliability of some content produced by AI, and the lack of clear institutional policy on the use of AI in higher education. To some extent, the lack of institutional policy also feeds into the lack of national policy on the use of AI for academic-related activities. Thus the position of Chan and Hu (2023) and Segbenya et al. (2023) that AI usage for academic activities comes with some challenges in higher education was upheld.

The findings of the first hypothesis that AI challenges are significantly related to productivity among academics in higher education means that the higher the challenges associated with the use of AI platforms the lower the productivity of these academics in higher education. Alternatively, the lower the challenges, the higher the productivity of academics in higher education. Thus, for higher productivity among academics in terms of using AI for research and teaching, the level of challenges will need to be on the lower side. The position of Atlas (2023) and Segbenya et al. (2023) that AI usage comes with some level of challenges to the users is supported by this study. While the previous studies found challenges with AI usage among graduate students, this study adds to the existing literature that academics/faculty members also experienced some challenges with the use of AI and some of these challenges were lack of institutional support in terms of resources, policy training on how to use AI in higher education among others.

Findings that the availability of AI tools did not relate to the productivity of lecturers in higher institutions recorded for hypothesis two means that any productivity of academics does share its predictability and potency with just the availability of AI tools. The result means that availability is important but was not adequate/enough to influence the productivity of academics. Thus, it is not enough to just be aware of the availability of the right AI tools, academics will need the competencies or skills to navigate these platforms to deliver on their jobs in terms of teaching and research and that could explain the non-significance relationship established. The findings of this study, therefore, did not support that of Baidoo-Anu and Ansah (2023) that technological availability impacts usage. It must be noted that the earlier findings were limited to learners, but the later findings of this study add to knowledge from faculty members' perspectives in terms of availability and productivity compared to the availability of AI apps.

The findings for hypothesis three that artificial intelligence tool availability significantly leads to usage among academics further explain hypothesis two that availability must be linked to usage before it can lead to productivity among academics. Thus, availability will need to be enhanced with information while usage will need to be enhanced with the necessary skills to use these AI tools. It therefore means that the more academics are aware of the various AI tools and can use them the higher they will use them for research and teaching-related activities in higher education. Therefore, the results of this investigation support those of Baidoo-Anu and Ansah (2023), who discovered that the accessibility of technological instruments affects utilization.

The fourth hypothesis also found that the use of AI affected academic productivity in higher education. The findings imply that the more effectively academics use AI tools appropriate for their particular research and teaching tasks, the more effectively they will fulfill their mandates to produce high-quality teaching and research outputs. This means that some aspects of the academics' job schedule such as searching for information, learning to understand some concepts, literature review, preparing PowerPoint, and writing commands for data analysis can be significantly improved with AI tools/platforms. This further confirms earlier findings that academics will need competencies in how to use these AI tools to improve their productivity or to deliver on their mandates. These findings remained a contribution to literature since this does not exist in the available literature.

The findings for hypothesis five that AI usage is also related to AI-associated challenge means that the degree of challenges encountered by academics in connection to AI tools can influence the level of usage. The lower the challenges associated with the AI tools available the higher the chances that usage will increase among academics. Thus, if the management of higher educational institutions reduces challenges such as lack of policies, resource support, and lack of training on how to use AI tools/platforms among others, then usage of AI among academics in higher education can increase.

Practical and theoretical implications

The outcome of this study has several implications for theory and practice. In terms of practice, it can be seen from the outcome of the study that AI has come to stay and will make an impact on work delivery including academics in the higher educational landscape. Thus, the first practical implication is for academics or faculty members is to have adequate and timely information on AI tools and how they can be used for both teaching and learning-related activities of the academics' mandates. Also, authorities of higher education should provide training to equip academics on how to use the available AI tools as well as provide logistical support and a clear policy to regulate the use of AI for academic activities in the higher education landscape. The last practical implication of the findings of this study is that though the use of AI could enhance the delivery of some aspects of the academics' job in terms of teaching and research, it is not without challenges and the level of these challenges can reduce the usage and also negatively affect the productivity of academics in higher education. The support of the management of higher educational institutions to reduce the level of challenges encountered by academics is required to enhance the usage of AI for teaching and research activities.

The results of this study clearly confirm the claim that artificial intelligence (AI) as technology progresses in higher education has both technical and societal ramifications, with regard to theoretical implications for the socio-technical theory that drove this study. That is the adoption and usage of AI among academics will need ICT infrastructure, technical support systems as well as clear policies and training for academics to properly use AI without compromising academic integrity.

Conclusion and recommendations

This study examined artificial intelligence and the productivity of academics in higher education. It can be concluded that the main AI tools/platforms known and used by academics for research and teaching-related activities were ChatGPT, OpenAI, and Quillbot. Academics hardly use AI software/platforms for extension activities. These AI tools were used mostly for general searches for information on course-related concepts, searching for course materials, and subjecting written text of students to plagiarism checks among others. It can also be concluded that benefits derived from the use of AI for research and teaching by academics in higher education include assisting in data analysis, improving educational content, gaining insight into research work, and improving the accuracy and efficiency of research findings. That notwithstanding, there were some challenges such as a lack of institutional support in terms of logistical support, training, and a clear policy on the use of AI in higher education. It is further concluded that the availability of AI tools leads to usage but does not directly lead to the productivity of academics. Challenges associated with AI usage were also found to have influenced productivity, and AI usage in higher education. Finally, AI usage was also found to have significantly influenced productivity among academics in higher education.

These conclusions demand clear steps to be taken by management and academics in higher education to enhance the use of AI for academic activities among faculty members in higher education. It is therefore recommended that the management of higher educational institutions should provide a clear policy on how AI should be adopted and used for academic work by both academics and students. A clear policy is needed to guard against academic dishonesty among both faculty members and postgraduate students. Furthermore, it is also recommended that the management of higher educational institutions provide adequate and timely information and training on the use of AI in higher education. These training and orientation programmes should be regular on how to adopt different AI tools for various aspects of the teaching and research activities and their delivery by academics. Training will not only equip these academics with the requisite skills but will also reinforce academics to easily adopt AI for academic-related activities. Also, The management of higher education institutions should also provide logistical support such as AI smart centres on various campuses where various AI tools/platforms are housed for individuals who cannot afford these technologies or do not have the online gadgets to be able to use the AI tools readily available. Academics in the various higher education institutions should also vary the nature of assignments given to students to include project or group-based practical activities that will encourage creativity and problem-solving among students. Academics in consultations with their employers should also adopt a similarity index cut-off point for every submission made by students and publications made by faculty members.

Limitations and suggestions for further studies

The findings of this study were only limited to academics in higher education. Any generalisation beyond the parameters of academics in higher education should be done with caution. Further studies, therefore, are proposed to be done on a more comprehensive scale to compare the views of academics, postgraduate students, and administrative staff in a single study on AI usage and productivity. This study is also limited to direct correlations between the variables investigated, thus, further studies could be done to determine the indirect (mediation and moderation) effect of gender and usage on AI tool availability and productivity of academics in higher education.

Informed consent

This study used a Google form questionnaire, which was created from the approved questionnaire and sent to each respondent separately. Since each respondent owned their own mobile phone, they were free to choose whether or not to participate in the study by answering the Google form.

Disclosure statement

The authors of this paper have no competing interests.

Funding

There is no funding for this study.

About the authors

Moses Segbenya holds a doctorate in Development Studies (Human Resource Development) from the University of Cape Coast and the University of Kassel, Germany. He is currently a Senior Lecturer at the Department of Business Studies, College of Distance Education (CoDE), University of Cape Coast (UCC). Moses Segbenya is currently the Coordinator of Postgraduate Programmes and a former Coordinator of the Arts and Social Sciences Unit, CoDE, UCC. He has published and served as a reviewer for Scopus Journals from reputable publishers like Emerald, Elsevier, Taylor and Francis, Sage, and Wiley among others. He has attended and presented papers at several local and international conferences in Mexico, Germany, South Africa, Egypt, and Kenya among others. His research interests include human resource issues in distance education, working conditions, informal workers, retention, and human resource information systems.

Felix Senyametor holds Ph.D. in Educational Psychology and other qualification in Education. He is a Senior Lecturer at the Department of Education and Psychology, Faculty of Educational Foundations, University of Cape Coast. His research interest areas are distance education, teacher motivation, instructional quality, and teacher effectiveness. Felix Senyametor published and served as a reviewer for Scopus Journals from reputable publishers like Emerald, Elsevier, Taylor and Francis among others.

Simon-Peter Kafui Aheto holds a doctorate in Information Technology and other qualifications in Education and Law. He is a Senior Lecturer of Educational & Information Technology at the Department of Distance Education and Coordinator for international Programmes at the College of Education at the University of Ghana. He is the Lead researcher for UNESCO's Internet Universality Indicators Assessment on Ghana. His interests include rhizomatic learning, educational law, gender, learning analytics, social network analysis, open and distance learning, educational law, entrepreneurship education, and youth development.

Edmond Kwesi Agormedah is an educator and a lecturer of Management Education at the Department of Business and Social Sciences Education, University of Cape Coast, Ghana. He holds a PhD in Management Education. Presently, he is a lecturer at the same Department, serving as a member of the Faculty Financial Committee and Thesis Vetting and Seminars Committee. He has supervised and assessed a number of postgraduate theses and undergraduate project works. He has research interests in Management Education, Curriculum and Instruction, Teacher Education, School Leadership and Management, and Educational Assessment and Evaluation. He has published and served as a reviewer for Scopus journals from reputable publishers including Sage Opens, Springer Opens, Taylor and Francis, and Frontiers among others. He has attended and presented papers at several local and international conferences.

Kwame Nkrumah is a Ph.D. candidate with the University of Cape Coast. He is Assistant Lecturer with the Department of Education, College of distance Education, University of Cape Coast. He has attended and presented papers at several conferences. His research interest include distance education, curriculum development, teaching, teacher motivation, instructional quality.

Rebecca Kaedebi-Donkor is a Ph.D. candidate with the University of Cape Coast. She is Assistant Lecturer with the Department of Education and Psychology, Faculty of Educational Foundations, University of Cape Coast, Cape Coast, Ghana. She has attended and presented papers at several conferences. His research interest include distance education, Science Education, teaching, teacher motivation, instructional quality.

ORCID

Moses Segbenya http://orcid.org/0000-0003-0065-2183
Simon-Peter Kafui Aheto http://orcid.org/0000-0001-9777-6005

Data availability statement

The datasets for this study are available from the corresponding author upon reasonable request.

References

Aheto, S. P. K., Barfi, K. A., Kwesi, C., & Nyagorme, P. (2024). Relationships between online self-regulation skills, satisfaction, and perceived learning among distance education learners. *Heliyon, 10*(8), 1–18. https://doi.org/10.1016/j.heliyon.2024.e29467

Al Husseiny, F. (2023). Artificial intelligence in higher education: A new horizon. In *Handbook of research on AI methods and applications in computer engineering* (pp. 295–315). IGI Global.

Alhussein, K. (2022). Responsible artificial intelligence. Challenges in research, university, and society. *Journal of Engineering and Technology Management*, *18*(3–4), 271–291.

Atlas, S. (2023). *ChatGPT for higher education and professional development: A guide to conversational AI*. Available at: https://digitalcommons.uri.edu/cba_facpubs/548

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4337484

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, *21*(1), 4. https://doi.org/10.1186/s41239-023-00436-z

Caffey, S., Venkatraj, V., Dixit, M. K., Yan, W., Sideris, P., & Aryal, A. (2023). Toward the application of a machine learning framework for building life cycle energy assessment. *Energy and Buildings, 297*, 113444.

Chaka, C. (2022). Fourth industrial revolution: A review of applications, prospects, and challenges for Artificial Intelligence, robotics, and blockchain in higher education. *Research and Practice in Technology Enhanced Learning*, *18*, 002–002. https://doi.org/10.58459/rptel.2023.18002

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43–63. https://doi.org/10.1186/s41239-023-00411-8

Chiancone, C. (2023). AI: The future of education harnessing AI to empower students. https://www.linkedin.com/pulse/ai-future-education-harnessing-empower-tudents-Chris-chance

Coffey, L. (2023). U.S. Lags in AI Use Among Students, Surveys Find. https://www.insidehighered.com/news/tech-innovation/artificialintelligence/2023/11/21/us-students-among-lowest-world-ai-usage

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Dabija, D. C., & Vătămănescu, E. M. (2023). Artificial intelligence: The future is already here. *Oeconomia Copernicana*, *14*(4), 1053–1056. https://doi.org/10.24136/oc.2023.031

Donkor, J., & Segbenya, M. (2023). Modelling the relationship between dimensions of organisational justice and organisational citizenship behaviour in the Ghanaian workplaces. *Employee Responsibilities and Rights Journal*, 1–22. https://doi.org/10.1007/s10672-023-09477-y

Georgieva, K. (2024). AI will transform the global economy. Let's make sure it benefits humanity.https://www.imf.org/en/Blogs/Articles/2024/01/14/ai-will-transform-the-global-economy-lets-make-sure-it-benefits-humanity

Hair, J. F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modelling (PLS-SEM)* (2nd Ed). Sage Publications Inc.

Hashmi, N., & Bal, A. S. (2024). Generative AI in higher education and beyond. *Business Horizons*, *2*(2), 1–18. https://doi.org/10.1016/j.bushor.2024.05.005

Hazaimeh, M., & Al-Ansi, A. M. (2024). Model of AI acceptance in higher education: Arguing teaching staff and students perspectives. *The International Journal of Information and Learning Technology*, *3*(2), 2056–4880. https://doi.org/10.1108/IJILT-01-2024-0005

Hutson, J., Jeevanjee, T., Graaf, V. V., Lively, J., Weber, J., Weir, Gr. a. ham., Arnone, K., Carnes, G., Vosevich, K., Plate, D., Leary, M., & Edele, S. u. san (2022). Artificial Intelligence and the disruption of higher education: Strategies for integrations across disciplines. *Creative Education*, *13*(12), 3953–3980. https://doi.org/10.4236/ce.2022.1312253

Jadagu, G. (2023). How AI is impacting and reshaping the academic landscape. https://www.researchgate.net/publication/374023526_How_AI_is_impacting_and_reshaping_the_academia_landscape/citations, https://doi.org/10.13140/RG.2.2.28698.82887

Jafari, F., & Keykha, A. (2023). Identifying the opportunities and challenges of artificial intelligence in higher education: A qualitative study. *Journal of Applied Research in Higher Education*, *16*(4), 1228–1245. https://doi.org/10.1108/JARHE-09-2023-0426

Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, *13*(18), 10424. https://doi.org/10.3390/su131810424

Kumar, S., Rao, P., Singhania, S., Verma, S., & Kheterpal, M. (2024). Will artificial intelligence drive the advancements in higher education? A tri-phased exploration. *Technological Forecasting and Social Change*, *201*, 123258. https://doi.org/10.1016/j.techfore.2024.123258

Lazaroiu, G., & Rogalska, E. (2023). How generative artificial intelligence technologies shape partial job displacement and labor productivity growth. *Oeconomia Copernicana*, *14*(3), 703–706. https://doi.org/10.24136/oc.2023.020

Leal Filho, W., Ribeiro, P. C. C., Mazutti, J., Lange Salvia, A., BonATo Marcolin, C., Lima Silva Borsatto, J. M., Sharifi, A., Sierra, J., Luetz, Joha. n. nes., Pretorius, R., & Viera Trevisan, L. (2024). Using artificial intelligence to implement the UN sustainable development goals at higher education institutions. *International Journal of Sustainable Development & World Ecology*, 1–20. https://doi.org/10.1080/13504509.2024.2327584

McGrath, C., Pargman, T. C., Juth, N., & Palmgren, P. J. (2023). University teachers' perceptions of responsibility and artificial intelligence in higher education-An experimental philosophical study. *Computers and Education: Artificial Intelligence*, *4*, 100139. https://doi.org/10.1016/j.caeai.2023.100139

Miao, F., Yang, W., Xie, Y., & Fan, W. (2023). *Preliminary study on data governance in data resource system* [Paper presentation]. In 2023 6th International Conference on Artificial Intelligence and big data (ICAIBD) (pp. 47–53). IEEE. https://doi.org/10.1109/ICAIBD57115.2023.10206189

Molleman, E., & Broekhuis, M. (2001). Sociotechnical systems: Towards an organizational learning approach. *Journal of Engineering and Technology Management*, *18*(3–4), 271–294.

Ocaña-Fernández, Y., Valenzuela-Fernández, L. A y., & Garro-Aburto, L. L. (2019). Inteligencia artificial y sus implicaciones en la educación superior. *Propósitos y Representaciones*, *7*(2), 536–568. https://doi.org/10.20511/pyr2019.v7n2.274

Oppong, N. Y., & Segbenya, M. (2023). Inter-sector managerial skills requirements in Ghana: Group interactive brainstorming approach. *Social Sciences & Humanities Open*, *8*(1), 100594. https://doi.org/10.1016/j.ssaho.2023.100594

Osman, Z., Alwi, N. H., Jodi, K. H. M., Khan, B. N. A., Ismail, M. N., & Yusoff, Y. (2024). Optimizing artificial intelligence usage among academicians in higher education institutions. *International Journal of Academic Research in Accounting, Finance & Management Sciences*, *1 4*(2), 12–29.

Peters, M. A., Jackson, L., Papastephanou, M., Jandrić, P., Lazaroiu, G., Evers, C. W., … Fuller, S. (2023). AI and the future of humanity: ChatGPT-4, philosophy and education–critical responses. *Educational Philosophy and Theory*, *55*(1), 1–14. https://doi.org/10.1080/00131857.2023.2213437

Rahiman, H. U., & Kodikal, R. (2024). Revolutionizing education: Artificial intelligence empowered learning in higher education. *Cogent Education*, *11*(1), 1–21. https://doi.org/10.1080/2331186X.2023.2293431

Rasul, T., Nair, S., Kalendra, D., Robin, M., de Oliveira Santini, F., Ladeira, W. J., … Heathcote, L. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning and Teaching*, *6*(1), 1–17.

Rawas, S. (2024). ChatGPT: Empowering lifelong learning in the digital age of higher education. *Education and Information Technologies*, *29*(6), 6895–6908. https://doi.org/10.1007/s10639-023-12114-8

Saaida, M. B. (2023). AI-Driven transformations in higher education: Opportunities and challenges. *International Journal of Educational Research and Studies*, *5*(1), 29–36.

Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: A systematic review. *International Journal of Educational Technology in Higher Education*, *19*(1), 21–42. https://doi.org/10.1186/s41239-022-00326-w

Schiller International University [SIU]. (2023). The Impact of artificial intelligence on higher education: How it is transforming learning https://schiller.edu/blog/the-impact-of-artificial-intelligence-on-higher-education-how-it-is-transforming-learning

Segbenya, M., & Anokye, F. A. (2023). Challenges and coping strategies among distance education learners: Implication for human resources managers. *Current Psychology (New Brunswick, N.J.)*, *42*(31), 1–15. https://doi.org/10.1007/s12144-022-03794-5

Segbenya, M., Atadika, D., Aheto, S. P. K., & Nimo, E. B. (2023). Modelling the relationship between teaching methods, assessment methods and acquisition of 21st employability skills among university graduates. *Industry and Higher Education*, *37*(6), 810–824. 09504222231175433. https://doi.org/10.1177/09504222231175433

Segbenya, M., Bervell, B., Frimpong-Manso, E., Otoo, I. C., Andzie, T. A., & Achina, S. (2023). Artificial intelligence in higher education: Modelling the antecedents of artificial intelligence usage and effects on 21st-century employability skills among postgraduate students in Ghana. *Computers and Education: Artificial Intelligence*, *5*, 100188. https://doi.org/10.1016/j.caeai.2023.100188

Segbenya, M., & Minadzi, V. M. (2023). Post-COVID lockdown assessment of blended learning approach for distance education in Ghana: Implications for human resource managers and curriculum implementers. *Education and Information Technologies*, *28*(7), 1–19. https://doi.org/10.1007/s10639-022-11516-4

Segbenya, M., Oduro, G. K. T., Peniana, F., & Ghansah, K. (2019). Proximity and choice of college of distance education (CoDE) of the University of Cape Coast for further studies. *International Journal of Educational Management*, *33*(5), 1012–1034. https://doi.org/10.1108/IJEM-12-2017-0379

Segbenya, M., & Okorley, E. N. A. (2022). Effect of teleworking on working conditions of workers: A Post-COVID-19 Lockdown Evaluation. *Human Behavior and Emerging Technologies*, *2022*(1), 1–14. 4562263. https://doi.org/10.1155/2022/4562263

Segbenya, M., Oppong, N. Y., & Baafi-Frimpong, S. A. (2021). The role of national service in enhancing employability skills of tertiary graduates in Ghana: A case of national service personnel in the Central Region. *Higher Education, Skills and Work-Based Learning*, *11*(5), 1089–1105. https://doi.org/10.1108/HESWBL-07-2020-0162

Segbenya, M., Oppong, N. Y., Nyarko, E. A., & Baafi-Frimpong, S. A. (2023). Demographic characteristics and employability skills among tertiary graduates in Ghana: Evidence from the National Service Scheme. *Cogent Economics & Finance*, *11*(2), 22–44. https://doi.org/10.1080/23322039.2023.2225915

Segbenya, M., Oppong, N. Y., & Nyieku, I. E. (2022). Elements of working conditions and retention of course tutors in distance education in Ghana. *Journal of Business and Enterprise Development (JOBED)*, *10*, 30–50. https://doi.org/10.47963/jobed.v10i.888

Tambuskar, S. (2022). Challenges and benefits of 7 ways artificial intelligence in education sector. https://www.researchgate.net/publication/373126618_Challenges_and_Benefits_of_7_ways_Artificial_Intelligence_in_Education_Sector

Thomas, G., Gambari, A. I., Sobowale, F. M., & Shehu, B. A. (2024). *Assessment of lecturers' utilization of artificial intelligence for education in a Nigerian University*. Iconic Open University workers: A post-COVID-19 lockdown evaluation. *Human Behavior and Emerging Technologies*, 1–23.

Yahaya, R., & Segbenya, M. (2023). Modelling the influence of managerial competence on managerial performance in the Ghanaian banking sector. *Humanities and Social Sciences Communications*, *10*(1), 1–11. https://doi.org/10.1057/s41599-023-02384-5

Yildiz, D. H. (2023). Conversational agent-based guidance: Examining the effect of chatbot usage frequency and satisfaction on visual design self-efficacy, engagement, satisfaction, and learner autonomy. *Education and Information Technologies*, *28*(1), 471–488.