



Investigating Undergraduate Students' Intention to Engage in Artificial Intelligence Learning

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Abstract: This study examines how contextual factors and influences shape undergraduate students' attitudes and behaviors regarding artificial intelligence (AI) learning. Globally, AI is becoming increasingly important in education, making it imperative to understand the readiness and intentions of students for AI-enhanced learning. One hundred and ninety-two higher education students in Nigeria were surveyed online about their confidence, attitudes, self-efficacy, and age—the relationships between these factors and students' intentions to learn through AI were analysed using structural equation modelling. A significant direct association was found between confidence, attitudes, self-efficacy, and subjective norms and the intention of students to use AI. Mediation analyses demonstrated that attitudes significantly mediate the relationship between subjective norms and intention. Perceived usefulness is therefore of paramount importance. Despite this, age does not play a significant role in modifying these relationships. A review of the study's quality criteria, including fit indexes and reliability measures, indicated that the model reasonably fit the data. The study provides valuable insights into the factors influencing undergraduate students' intentions to engage in AI learning.



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Introduction

Artificial intelligence (AI) and its subfield, machine learning, have experienced rapid growth in recent years, particularly in the context of data analysis and computing, enabling applications to function intelligently.¹ Research has been conducted extensively

¹ Sarker, I. H. "AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems." *SN Computer Science* 3, no. 2 (2022): 158.

on AI, particularly in higher education.² A major challenge in Science Technology Engineering and Mathematics education is effectively integrating various AI techniques and multidimensional educational elements to support instructional and learning needs.³ Molenaar⁴ asserted that in academic settings, AI has historically aimed to assist students by providing them with an intelligent tutor, thereby offloading the work of teachers to computers with AI. Furthermore, Crompton and Song⁵ noted that AI's potential to extend and enhance teaching and learning in higher education has been highlighted.

There has been considerable interest in integrating AI into education from the government, schools, academia, and industry, reflecting global interest in this area.⁶ As part of a strategic move to educate the next generation, Yau et al.⁷ stated that it has become imperative for K-12 students to be equipped with basic AI knowledge. The emphasis is on integrating AI education into school curricula. In addition, Peng et al.⁸ opined that AI education is recognised as a valuable method of cultivating students' comprehensive thinking abilities. Lukianets and Lukianets⁹ averred that implementing AI in education is expected to facilitate educational processes, increase enrolment and retention, and enhance educational opportunities. There are, however, challenges to AI education, such as economic inequity resulting from its reliance on computational infrastructure and equipment.¹⁰

Furthermore, ethical application issues are growing increasingly critical,

<https://doi.org/10.1007/s42979-022-01043-x>.

² Zawacki-Richter, O., Marín, V. I., Bond, M. and Gouverneur, F. "Systematic review of research on artificial intelligence applications in higher education – where are the educators?" *International Journal of Educational Technology in Higher Education* 16, no. 1 (2019): 39. <https://doi.org/10.1186/s41239-019-0171-0>.

³ Xu, W. and Ouyang, F. "The application of AI technologies in STEM education: A systematic review from 2011 to 2021." *International Journal of STEM Education* 9, no. 59 (2022). <https://doi.org/10.1186/s40594-022-00377-5>.

⁴ Molenaar, I. "The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning." *Computers and Education: Artificial Intelligence* 3, (2022): 100070. <https://doi.org/10.1016/j.caeai.2022.100070>

⁵ Crompton, H. and Song, D. "The potential of artificial intelligence in higher education." *Revista Virtual Universidad Católica Del Norte* 62, (2021): 1–4. <https://doi.org/10.35575/rvucn.n62a1>.

⁶ Song, J., Zhang, L., Yu, J., Peng, Y., Ma, A. and Lu, Y. "Paving the way for novices: How to teach AI for K-12 education in China." *Proceedings of the AAAI Conference on Artificial Intelligence* 36, no. 11 (2022): 12852–12857. <https://doi.org/10.1609/aaai.v36i11.21565>.

⁷ Yau, K. W., Chai, C. S., Chiu, T. K. F., Meng, H., King, I. and Yam, Y. "A phenomenographic approach on teacher conceptions of teaching artificial intelligence (AI) in K-12 schools." *Education and Information Technologies* 28, no. 1 (2023): 1041–1064. <https://doi.org/10.1007/s10639-022-11161-x>.

⁸ Peng, M., Xie, J., Xiong, M. and Liu, Y. "Artificial Intelligence education in primary and secondary schools from the perspective of thinking quality." *Journal of Contemporary Educational Research* 7, no. 4 (2023): 41–46. <https://doi.org/10.26689/jcer.v7i4.4875>.

⁹ Lukianets, H. and Lukianets, T. "Promises and perils of AI use on the tertiary educational level." *Grail of Science* 25, (2023): 306–311. <https://doi.org/10.36074/grail-of-science.17.03.2023.053>.

¹⁰ Wu, C., Li, Y., Li, J., Zhang, Q. and Wu, F. "Web-based platform for K-12 AI education in China." *Proceedings of the AAAI Conference on Artificial Intelligence* 35, no. 17 (2021): 15687–15694. <https://doi.org/10.1609/aaai.v35i17.17848>.

particularly in healthcare and medical education areas where AI is applied.¹¹ It is essential to note that certain factors may hinder students' intentions to use AI. For example, a study on medical students found that they believed using AI in medicine increased the risks for patients and the medical community.¹² The global integration of AI in education reflects a transformative shift towards leveraging advanced technologies to enhance learning experiences, improve educational processes, and cultivate a more inclusive and engaging educational environment. While the potential benefits of AI in education are substantial, it is crucial to address challenges such as economic inequity, ethical considerations, and the need for comprehensive infrastructure to ensure the responsible and effective implementation of AI technologies in educational settings.

Overview of AI in Global Development

Artificial Intelligence (AI) adoption attitudes have significantly impacted companies' ability to meet changing demands and remain competitive within the building and environment industry.¹³ Furthermore, AI has been recognised as a technology capable of integrating human behavior into machines and systems. Thus, it is considered a leading technology in the Fourth Industrial Revolution.¹⁴ The use of AI among students in various fields, such as medicine, nursing, psychology, and education, has been the subject of several studies. These studies have identified factors that influence students' attitudes and perceptions towards AI and their intention to use AI in their future careers. For example, a survey of UK medical students revealed that those who received teaching in AI were more likely to consider radiology and had a more positive perception of using AI in post-graduation healthcare.¹⁵

Similarly, a study on Chinese secondary school students found that self-efficacy and perception of using AI to promote social good influenced their intention to learn AI.¹⁶

¹¹ Leimanis, A. and Palkova, K. "Ethical guidelines for artificial intelligence in healthcare from the sustainable development perspective." *European Journal of Sustainable Development* 10, no. 1 (2021): 90. <https://doi.org/10.14207/ejsd.2021.v10n1p90>.

¹² Mousavi, B., Seyyede, F., Sarbaz, M., Ghaddaripouri, K., Ghaddaripouri, M., Mousavi, A. S. and Kimiafar, K. "Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: A systematic review." *Health Science Reports* 6, no. 3 (2023). <https://doi.org/10.1002/hsr2.1138>.

¹³ Shang, G., Low, S. P. and Lim, X. Y. V. "Prospects, drivers of and barriers to artificial intelligence adoption in project management." *Built Environment Project and Asset Management* 13, no. 5 (2023): 629–645. <https://doi.org/10.1108/BEPAM-12-2022-0195>.

¹⁴ Sarker, "AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems," 158.

¹⁵ Sit, C., Srinivasan, R., Amlani, A., Muthuswamy, K., Azam, A., Monzon, L. and Poon, D. S. "Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: A multicentre survey." *Insights into Imaging* 11, no. 1 (2020): 14. <https://doi.org/10.1186/s13244-019-0830-7>.

¹⁶ Chai, C. S., Lin, P.-Y., Jong, M. S., Dai, Y., Chiu, T. K. F. and Huang, B. "Factors influencing students'

Furthermore, a study on prospective physicians highlighted the dominance of social influence on the intention to use AI for future work among undergraduate medical students.¹⁷ In the context of nursing, it was found that nursing students' attitudes, self-efficacy, and intentions to use AI are crucial for preparing them to adapt to technological changes in nursing.¹⁸ In addition, a study on psychology students suggested interventions to foster their intention to use AI, such as providing specific insights into the application areas of AI to raise their curiosity and broaden their experiences with AI technology.¹⁹ Moreover, Wagner et al.'s²⁰ study of physicians in training's intentions to use AI in their future medical practice indicated that certain AI profiles, combinations of knowledge and experience, attitudes and beliefs, academic level, and gender were associated with high intentions to use AI in the future.

Artificial Intelligence (AI) has become an increasingly significant tool in education globally, focusing on various aspects such as STEM education, K-12 education, and higher education. Integrating AI into education aims to enhance learning experiences, optimise educational processes, and improve learning efficiency.²¹ The application of AI in education is not limited to a specific region as it has attracted considerable attention from various countries, including China and South Korea.^{22,23} Reports indicate that AI will be implemented in higher education within the next four to five years, signifying AI's rapid development and adoption in educational institutions.²⁴ Artificial Intelligence (AI) technologies have been used to create more personalized, flexible, and inclusive learning experiences, reflecting the potential to cultivate students' comprehensive thinking

behavioral intention to continue artificial intelligence learning." 2020 *International Symposium on Educational Technology (ISET)* (2020a): 147–150. <https://doi.org/10.1109/ISET49818.2020.00040>.

¹⁷ Tran, A. Q., Nguyen, L. H., Nguyen, H. S. A., Nguyen, C. T., Vu, L. G., Zhang, M., Vu, T. M. T., Nguyen, S. H., Tran, B. X., Latkin, C. A., Ho, R. C. M. and Ho, C. S. H. "Determinants of intention to use artificial intelligence-based diagnosis support system among prospective physicians." *Frontiers in Public Health* 9, (2021). <https://doi.org/10.3389/fpubh.2021.755644>.

¹⁸ Kwak, Y., Ahn, J.-W. and Seo, Y. H. "Influence of AI ethics awareness, attitude, anxiety, and self-efficacy on nursing students' behavioral intentions." *BMC Nursing* 21, no. 1 (2022): 267. <https://doi.org/10.1186/s12912-022-01048-0>.

¹⁹ Gado, S., Kempen, R., Lingelbach, K. and Bipp, T. "Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence?" *Psychology Learning & Teaching* 21, no. 1 (2022): 37–56. <https://doi.org/10.1177/14757257211037149>.

²⁰ Wagner, G., Raymond, L. and Paré, G. "Understanding prospective physicians' intention to use artificial intelligence in their future medical practice: Configurational analysis." *JMIR Medical Education* 9, (2023): e45631. <https://doi.org/10.2196/45631>.

²¹ Lukianets and Lukianets, "Promises and perils of AI use on the tertiary educational level," 306–311.

²² Park, W. and Kwon, H. "Implementing artificial intelligence education for middle school technology education in Republic of Korea." *International Journal of Technol Design Education* 34, (2024): 109–135. <https://doi.org/10.1007/s10798-023-09812-2>.

²³ Song, Zhang, Yu, Peng, Ma, and Lu, "Paving the way for novices: How to teach AI for K-12 education in China," 12852–12857.

²⁴ Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P. and Romero-Rodríguez, J. M. "Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature." *Education Sciences* 9, no. 1 (2019): 51.

quality and improve their learning outcomes.^{25,26}

Furthermore, AI has been identified as a core technology that enables a knowledge and information-led society, emphasising its role in shaping the future of education.²⁷ The potential of AI in education extends beyond traditional classroom settings, as it has been leveraged to develop online education systems and autonomous learning platforms, thereby expanding the scope of education and knowledge mastery.^{28,29} However, integrating AI into education also presents challenges, particularly regarding economic inequity and the need for computational infrastructure and equipment.^{30,31} In addition, ethical considerations have become increasingly important, especially in healthcare and medical education areas where AI is applied.³² As AI continues to evolve and expand its influence, it is essential to address ethical application issues and ensure that AI technologies are implemented responsibly in educational settings. Artificial Intelligence (AI) technology has extended beyond the information technology industry, with its use being witnessed across various industries, including tourism, hospitality, and intelligent manufacturing.

Artificial Intelligence (AI) related technologies benefit manufacturing firms and are well recognised. Unfortunately, there is a lack of industrial AI maturity models that can assist companies in assessing their current state and planning for the future.³³ Moreover, integrating AI and the Internet of Things in the power generation and distribution industry presents opportunities and challenges, particularly regarding cybersecurity.³⁴ According to a survey of medical students and professionals, medical

²⁵ Peng, M., Xie, J., Xiong, M. and Liu, Y. "Artificial Intelligence education in primary and secondary schools from the perspective of thinking quality." *Journal of Contemporary Educational Research* 7, no. 4 (2023): 41–46.

²⁶ Yildirim, H., Barut, M. and Gungor, O. "Artificial intelligence in accounting: Evaluation and practices." *Journal of Artificial Intelligence in Accounting* 8, no. 3 (2021): 123–145. <https://doi.org/10.1016/j.artintacct.2021.05.001>.

²⁷ Lee, J. and Cho, H. "The impact of artificial intelligence on the future of accounting." *Journal of Emerging Technologies in Accounting* 18, no. 2 (2021): 89–108. <https://doi.org/10.2308/jeta-2021-0045>.

²⁸ Hua, W. "Exploring the role of artificial intelligence in financial decision-making: Challenges and opportunities." *Journal of Financial Technology and AI* 10, no. 1 (2022): 55–72. <https://doi.org/10.1016/j.jftai.2022.01.003>.

²⁹ Zhang, L. "AI-driven innovations in accounting: A review of recent developments." *International Journal of Accounting and AI* 15, no. 4 (2023): 201–219. <https://doi.org/10.1080/ijaa.2023.01452>.

³⁰ Çakmak, F. "Chatbot-human interaction and its effects on EFL students' L2 speaking performance and speaking anxiety." *Novitas-ROYAL (Research on Youth and Language)* 16, no. 2 (2022): 113–131.

³¹ Wu, Li, Li, Zhang, and Wu, "Web-based platform for K-12 AI education in China," 15687–15694.

³² Leimanis and Palkova, "Ethical guidelines for artificial intelligence in healthcare from the sustainable development perspective," 90.

³³ Chen, W., Liu, C., Xing, F., Peng, G. and Yang, X. "Establishment of a maturity model to assess the development of industrial AI in smart manufacturing." *Journal of Enterprise Information Management* 35, no. 3 (2022): 701–728. <https://doi.org/10.1108/JEIM-10-2020-0397>.

³⁴ Mohamed, N., Oubelaid, A. and Almazrouei, S. khameis. "Staying ahead of threats: A review of

students are more likely to experience identity threats and resistance to AI than medical professionals.³⁵ Despite the increasing relevance of AI in various industries, challenges such as trust requirements and the need for explainable AI models have been identified, making it challenging to understand how AI works.^{36,37}

Factors Influencing Students' Intentions to Engage in AI Learning

Students' intentions to engage in AI depend on several factors, and the technology acceptance model (TAM) provides an understanding of how users accept technologies.³⁸ Students' knowledge of AI, general AI anxiety, and subjective norms influence their attitudes towards AI learning and behavioral intentions.^{39,40} The TAM measures perceived usefulness and ease of use as predictors of user intent to use computer technology.⁴¹ In addition, the extended TAM explains perceived usefulness and usage intentions concerning social influence and cognitive process considerations.⁴² Autonomy influences students' intention to learn AI.⁴³ and intrinsic and extrinsic motivation, perception of multiple sources, and cognitive engagement contribute to students' continuous intention to use online courses, which could be relevant to AI teaching.⁴⁴

AI and cyber security in power generation and distribution." *International Journal of Electrical and Electronics Research* 11, no. 1 (2023): 143–147. <https://doi.org/10.37391/ijeer.110120>.

³⁵ Mousavi, Seyyedeh, Sarbaz, Ghaddaripouri, Ghaddaripouri, Mousavi and Kimiafar, "Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: A systematic review".

³⁶ Bedué, P. and Fritzsche, A. "Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption." *Journal of Enterprise Information Management* 35, no. 2 (2022): 530–549. <https://doi.org/10.1108/JEIM-06-2020-0233>.

³⁷ Yang, M., Moon, J., Yang, S., Oh, H., Lee, S., Kim, Y. and Jeong, J. "Design and implementation of an explainable bidirectional LSTM model based on transition system approach for cooperative AI-workers." *Applied Sciences* 12, no. 13 (2022): 6390. <https://doi.org/10.3390/app12136390>.

³⁸ McCord, M. Technology acceptance model. In *Handbook of research on electronic surveys and measurements* (2007): 306–308. IGI Global. <https://doi.org/10.4018/978-1-59140-792-8.ch038>.

³⁹ Chai, C. S., Wang, X. and Xu, C. "An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn artificial intelligence." *Mathematics* 8, no. 11 (2020b): 2089. <https://doi.org/10.3390/math8112089>.

⁴⁰ Yangin Ersanli, C. "The effect of using augmented reality with storytelling on young learners' vocabulary learning and retention." *Novitas-ROYAL (Research on Youth and Language)* 17, no. 1 (2023): 62–72.

⁴¹ McCord, "Technology acceptance model," 306–308.

⁴² Venkatesh, V. and Davis, F. D. "A theoretical extension of the technology acceptance model: Four longitudinal field studies." *Management Science* 46, no. 2 (2000): 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>.

⁴³ Chai, C. S., Chiu, T. K. F., Wang, X., Jiang, F. and Lin, X.-F. "Modeling Chinese secondary school students' behavioral intentions to learn artificial intelligence with the theory of planned behavior and self-determination theory." *Sustainability* 15, no. 1 (2022): 605. <https://doi.org/10.3390/su15010605>.

⁴⁴ Lu, K., Pang, F. and Shadiev, R. "Understanding college students' continuous usage intention of asynchronous online courses through extended technology acceptance model." *Education and Information Technologies* 28, no. 8 (2023): 9747–9765. <https://doi.org/10.1007/s10639-023-11591-1>.

Moreover, the theory of planned behavior (TPB) is valid for identifying factors affecting students' behavioral intentions toward learning AI in medical education.⁴⁵ These findings suggest that knowledge, anxiety, subjective norms, autonomy, motivation, and cognitive engagement influence students' intentions to engage in AI learning. Similarly, perceived usefulness and attitudes were found to be significant factors influencing students' intention to engage in technology, as echoed in previous TAM research.⁴⁶ Moreover, the extended TAM examines whether literacy tools, metacognitive self-regulation, subjective norms, facilitating conditions, and institutional support are associated with pre-service teachers' intentions to incorporate Web 2.0 technology into their courses.⁴⁷

In addition, university students' attitudes toward adopting collaborative technologies positively influenced their behavioral intentions to use e-learning platforms, which could apply to AI learning platforms.⁴⁸ Fu et al.⁴⁹ examined the continuous intention of AI-enabled learning tools by exploring various influencing factors, indicating the relevance of AI-enabled tools in influencing students' continuous learning intention. These studies suggest that students' attitudes toward technology adoption and the affordances of AI-enabled tools can significantly influence their intention to engage in AI learning.

Technology Acceptance Model

The TAM was initially proposed in 1989 and has since been widely used to understand and predict user acceptance of technology.⁵⁰ The model focuses on perceived usefulness and ease of use as critical determinants of user acceptance and intention to

⁴⁵ Li, X., Jiang, M. Y., Jong, M. S., Zhang, X. and Chai, C. Understanding medical students' perceptions of and behavioral intentions toward learning artificial intelligence: A survey study. *International Journal of Environmental Research and Public Health* 19, no. 14 (2022): 8733. <https://doi.org/10.3390/ijerph19148733>.

⁴⁶ Wang, X., Wang, P., Wang, P., Cao, M. and Xu, X. "Relationships among mental health, social capital and life satisfaction in rural senior older adults: A structural equation model." *BMC Geriatrics* 22, no. 1 (2022): 73. <https://doi.org/10.1186/s12877-022-02761-w>.

⁴⁷ Şimşek, A. S. and Ateş, H. "The extended technology acceptance model for Web 2.0 technologies in teaching." *Innoeduca. International Journal of Technology and Educational Innovation* 8, no. 2 (2022): 165–183. <https://doi.org/10.24310/innoeduca.2022.v8i2.15413>.

⁴⁸ Chang, Y., Lee, S., Wong, S. F. and Jeong, S. "AI-powered learning application use and gratification: An integrative model." *Information Technology & People* 35, no. 7 (2020b): 2115–2139. <https://doi.org/10.1108/ITP-09-2020-0632>.

⁴⁹ Fu, S., Gu, H. and Yang, B. "The affordances of AI-enabled automatic scoring applications on learners' continuous learning intention: An empirical study in China." *British Journal of Educational Technology* 51, no. 5 (2020): 1674–1692. <https://doi.org/10.1111/bjet.12995>.

⁵⁰ Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. "User acceptance of computer technology: A comparison of two theoretical models." *Management Science* 35, no. 8 (1989): 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>.

use technology^{51,52} In addition, the TAM has been integrated with other theories, such as the theory of reasoned action and the unified theory of acceptance and use of technology, to enhance its explanatory power.^{53,54} The TAM has been subject to extensive research, including bibliometric analysis and text mining, to trace its diffusion and evolution across disciplines.⁵⁵

However, some scholars have critically examined the limitations of TAM, calling for philosophical scrutiny of its applicability, particularly in the context of e-learning adoption.⁵⁶ Moreover, the TAM has been used to assess technology acceptance in various domains, such as pre-service teachers' intention to use technology and adopt cloud computing in organizations.^{57,58} The model has also been applied in diverse cultural contexts, with studies comparing the intention to use technology among pre-service teachers in Singapore and Malaysia.⁵⁹ The TAM has proven to be a valuable framework for understanding user acceptance of technology, with its widespread application and continuous evolution contributing to its enduring significance in technology acceptance research.

The influence of AI perception, expectancy, and perceived risk on clinicians' intention to use AI technology has been captured through structural equation modelling,

⁵¹ Venkatesh, V. and Bala, H. "Technology acceptance model 3 and a research agenda on interventions." *Decision Sciences* 39, no. 2 (2008): 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>.

⁵² Venkatesh and Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," 186–204.

⁵³ Hsiao, C.-H. and Tang, K.-Y. "Explaining undergraduates' behavior intention of e-textbook adoption." *Library Hi Tech* 32, no. 1 (2014): 139–163. <https://doi.org/10.1108/LHT-09-2013-0126>.

⁵⁴ Zolait, A., Radhi, N., Alhowaishi, M. M., Sundram, V. P. K. and Aldoseri, L. M. "Can Bahraini patients accept e-health systems?" *International Journal of Health Care Quality Assurance* 32, no. 4 (2019): 720–730. <https://doi.org/10.1108/IJHCQA-05-2018-0106>.

⁵⁵ Wang, F. and Wang, X. "Tracing theory diffusion: A text mining and citation-based analysis of TAM." *Journal of Documentation* 76, no. 6 (2020): 1109–1134. <https://doi.org/10.1108/JD-02-2020-0023>.

⁵⁶ Islam, A. K. M. N., Azad, N., Mäntymäki, M. and Islam, S. M. S. TAM and e-learning adoption: A philosophical scrutiny of TAM, its limitations, and prescriptions for e-learning adoption research. In H. Li, M. Mäntymäki & X. Zhang (Eds.), *Digital services and information intelligence. IFIP advances in information and communication technology* 445, (2014): 164–175. Springer. https://doi.org/10.1007/978-3-662-45526-5_16.

⁵⁷ Gangwar, H., Date, H. and Ramaswamy, R. "Developing a cloud-computing adoption framework." *Global Business Review* 16, no. 4 (2015): 632–651. <https://doi.org/10.1177/0972150915581108>.

⁵⁸ Teo, T., Lee, C. B., Chai, C. S. and Wong, S. L. "Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the technology acceptance model (TAM)." *Computers & Education* 53, no. 3 (2009): 1000–1009. <https://doi.org/10.1016/j.compedu.2009.05.017>.

⁵⁹ Teo, Lee, Chai, and Wong, "Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the technology acceptance model (TAM)," 1000–1009.

highlighting these factors' direct and indirect effects.⁶⁰ The TAM has also been widely used to examine individuals' acceptance of technology in various contexts. This includes preschool teachers' technology acceptance during the COVID-19 pandemic.⁶¹ In addition to positive effects, the TAM has also been extended to include negative effects, which allows for a more holistic understanding of technology acceptance.⁶²

Method

This study focuses on higher education students' intentions to use AI. These students were enrolled in colleges of education, polytechnics, and universities in Nigeria, a country located in Western Africa. Nigeria has an estimated 250 million people, making it the largest Black country in the world. It is equally important to consider the phenomenon among the target population in an African context, even though little is known about AI and higher education students' perspectives globally. Despite numerous challenges, Nigeria extensively uses Information and Communication Technology devices, the internet, and other emerging technologies. The context must be studied considering these factors and many others.

Sample Analytical Strategy

The study sample consisted of 192 students in higher institutions in colleges of education, polytechnics, and universities in Nigeria. The study employed snowball sampling techniques for recruiting 215 participants; 207 (96%) were eligible, 197 (95%) consented to participate as study respondents, and 192 (97%) completed the online survey form. This technique is particularly useful when the target population is inaccessible through traditional methods. Participants in this study were undergraduate students enrolled in various academic disciplines across multiple higher institutions. The inclusion criteria required participants to be undergraduate students during data collection. There were no restrictions based on age, gender, or academic major to ensure a diverse sample.

⁶⁰ Choudhury, A. "Toward an ecologically valid conceptual framework for the use of artificial intelligence in clinical settings: Need for systems thinking, accountability, decision-making, trust, and patient safety considerations in safeguarding the technology and clinicians." *JMIR Human Factors* 9, no. 2 (2022): e35421. <https://doi.org/10.2196/35421>.

⁶¹ Hong, X., Zhang, M. and Liu, Q. "Preschool teachers' technology acceptance during the COVID-19: An adapted technology acceptance model." *Frontiers in Psychology* 12, (2021): <https://doi.org/10.3389/fpsyg.2021.691492>.

⁶² Hoong, A. L. S., Thi, L. S. and Lin, M.-H. "Affective technology acceptance model: Extending technology acceptance model with positive and negative affect." *Knowledge Management Strategies and Applications*. (2017). <https://doi.org/10.5772/intechopen.70351>.

In our study, we conducted an online survey of participants who consented to participate. Several platforms were used to distribute the survey link (for example, WhatsApp). Since the survey link was distributed through a closed social media platform designed exclusively for communication between lecturers and students at participating institutions, it is believed that only students attending colleges of education, polytechnics, and universities filled out our survey. The survey form was designed to be filled out once. We selected our respondents using a snowball approach, and they represented the target population. We assumed this position as we had representation at all programme levels and across all three types of higher education institutions.

Those participating in the study were requested to fill out the survey with the assurance that their information would be kept confidential. The data collection was carried out between October and November 2022. The characteristics of participants who responded to the instrument are presented in Table 1.

Table 1. Characteristics of the Participants

Variable	Level	Frequency	Percentage
Age	16–19yrs	41	21.4
	20–23yrs	89	46.4
	24–26yrs	31	16.1
	27–29yrs	10	5.2
	30yrs and above	21	10.9
Gender	Male	65	33.9
	Female	127	66.1
Types of Institution	University	168	87.5
	Polytechnic	3	1.6
	College of Education	21	10.9
Familiar with AI	Yes	169	88.0
	No	23	12.0

As shown in Table 1, 33.9% of the respondents were males while 66.1% were females, so the proportion of female participants was more than that of males. Most respondents were aged 20–23 years (46.4%), 21.4% were aged 16–19 years, 16.1% were 24–26 years, 5.2% were 27–29 years and 10.9% were 30yrs and above. Also, the proportion of university students (87.5%) in the sample was more than that of students in the polytechnic (1.6%) and the college of education (10.9%). More so, most of the respondents (88.0%) were familiar with AI as opposed to 12.0% who were not.

Instruments

The measuring instrument used in this study was adapted from several literature sources. Two academic experts validated the questionnaire after it was adapted from earlier studies. Based on previous research, four latent variables were developed using 17 items.^{63,64} A Likert scale was used to rank responses from 1 (strongly disagree) to 6 (strongly agree). The survey instrument was divided into two parts. In the first part of the questionnaire, demographic information, such as gender, age, grade level, and area of specialization, was collected. The second part of the survey measured undergraduate students' confidence in learning using AI, attitudes toward learning using AI, self-efficacy in learning using AI, and intention to learn using AI. In addition, an ordinal alpha reliability coefficient (CON = 0.708, ATT = 0.710, SEE = 0.832, and INT = 0.817) and a content validity index (CON = 0.690, ATT = 0.710, SEE = 0.821, and INT = 0.804) were noted for each variable.

Analytical Strategy

Our research objectives were addressed using appropriate statistical methods to analyse the data. SmartPLS software version 4.0 was used. The validity and reliability of each construct considered in the questionnaire were examined using a measurement model. A structural model confirmed the significance and strength of the hypothesized relationships between the latent variables. Confirmatory factor analysis and a structural equation model were conducted based on our hypothesized model to establish relationships between the factors considered. The following hypotheses were put forth:

1. Higher education students' characteristics do not directly affect their intention to use AI.
2. Higher education students' characteristics do not significantly mediate the intention to use AI.
3. Higher education students' age has no significant moderating effects on their intention to use AI.

Result

⁶³ Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D. and Oyelere, S. S. "Teachers' readiness and intention to teach artificial intelligence in schools." *Computers and Education: Artificial Intelligence* 3, (2022): 100099. <https://doi.org/10.1016/j.caeai.2022.100099>.

⁶⁴ Chai, Lin, Jong, Dai, Chiu, and Huang, "Factors influencing students' behavioral intention to continue artificial intelligence learning," 147–150.

Reliability of the Instrument

The reliability of the study instrument was established alongside its construct validity. The reliability and construct validity statistics are presented in Table 2.

Table 2. Reliability and Construct Validity of the Constructs in the Instrument

	Cronbach's alpha	Composite reliability (rho_a)	Composite Reliability (rho_c)	Average variance extracted (AVE)
ATT	0.710	0.710	0.837	0.632
CON	0.690	0.708	0.810	0.518
INT	0.804	0.817	0.865	0.563
SEE	0.821	0.832	0.894	0.737
SUN	0.588	0.603	0.762	0.447

Table 2 shows that the Cronbach Alpha reliability coefficients of the instruments are about 7.0, except for the subjective norm (SUN), which is 0.58. The composite reliability coefficients of the instruments are all above 0.7, indicating that the instruments are reliable. Except for SUN, the AVE coefficients are above 0.5 compared with the standard of 0.5. The results indicate that the reliability and construct validity of the instruments are moderate.

Discriminant validity of the instruments

Discriminant validity measures the degree to which individuals construct an instrument that differs from one another. The discriminant validity of the instrument used for this study was established using the Fornell-Larcker and Heterotraits-Monotraits approaches. The Fornell-Larcker criterion follows the principle that for a construct to be said to have discriminant validity, the coefficient of the relationship among the constructs in the model should not be up to the square root of the AVE of the constructs in question⁶⁵ (Fornell & Larcker, 1981). The result of the coefficient of the relationship is presented in Table 3.

Table 3. Discriminant Validity using Fornell-Larcker Criterion

ATT	CON	INT	SEE	SUN

⁶⁵ Fornell, C. and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18, no. 1 (1981): 39-50.

ATT	0.795				
CON	0.705	0.720			
INT	0.666	0.616	0.751		
SEE	0.699	0.650	0.593	0.859	
SUN	0.391	0.400	0.481	0.309	0.668

The square root of AVE for ATT in Table 1 is 0.794, which is lower than the correlation between ATT and other constructs in the model. Also, the square root of AVE for CON was 0.719, which was lower than the correlation coefficient between CON and other constructs. This shows that Fornell-Larcker's criterion confirms the discriminant validity of the constructs. For a more reliable result of discriminant validity, the Heterotrait-Monotrait method was also used,⁶⁶ as presented in Table 4.

Table 4. Discriminant Validity using Heterotraits-Monotraits Method

	ATT	CON	INT	SEE	SUN
ATT					
CON	0.985				
INT	0.863	0.827			
SEE	0.913	0.848	0.723		
SUN	0.588	0.610	0.686	0.435	

This work is based on Henseler et al.'s⁶⁷ proposition that discriminant validity is established when the value of intercorrelation is less than the threshold of 0.85. Table 3 shows that only the intercorrelation of ATT with CON and ATT with SEE is above the threshold of 0.85. Thus, the constructs in the model have discriminant validity.

Result

The study hypothesized that individual confidence in learning AI could affect their subjective norms, attitudes, self-efficacy, and intention to learn using AI. The study also hypothesized that the age of the participants could moderate the relationship in the model. Age could influence the intention of an intelligent individual to learn using AI, and an individual with a negative or positive attitude could have such an intention. The model for the relationship is presented in Figure 1.

⁶⁶ Voorhees, C. M., Brady, M. K., Calantone, R. and Ramirez, E. "Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies." *Journal of the Academy of Marketing Science* 44, no. 1 (2016): 119–134. <https://doi.org/10.1007/s11747-015-0455-4>.

⁶⁷ Henseler, J., Ringle, C. M. and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43 (2015): 115-135. <https://doi.org/10.1007/s11747-014-0403-8>

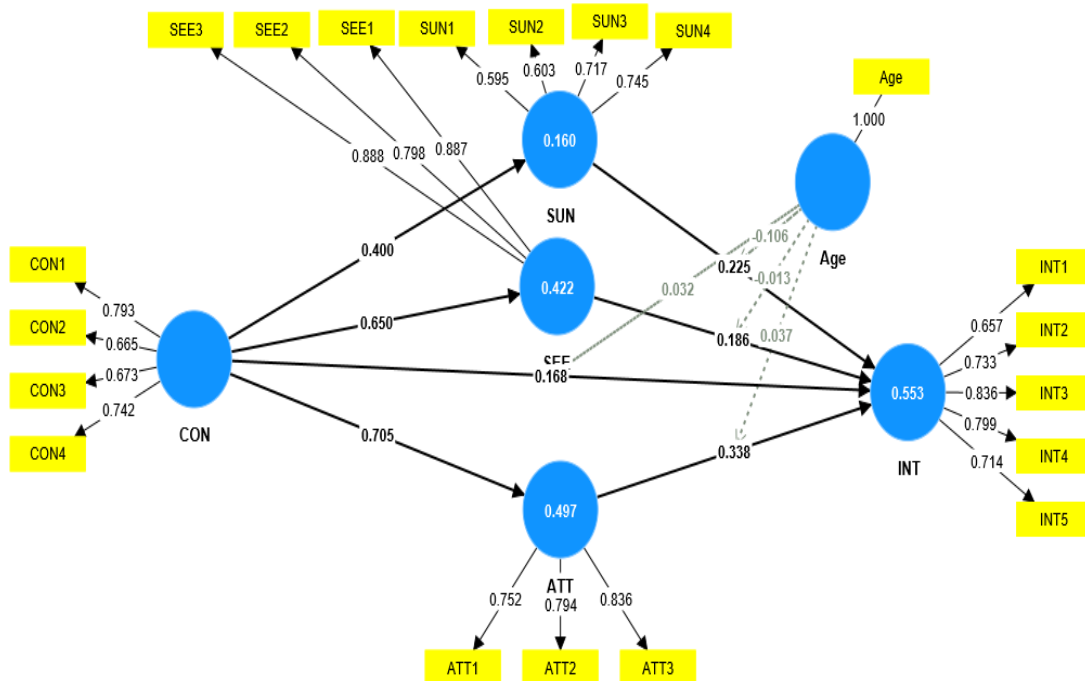


Figure 1. A PLS-structural Equation Model (SEM) for the Relationship Between Students' Characteristics and Intention to Use AI

The hypotheses in the study were tested by assessing the structure model using a bootstrapping technique with 5,000 iterations as suggested by Hair et al.⁶⁸ The direct effects were estimated to test the hypotheses about the direct relationship between two variables. In contrast, moderation and mediation effects were established by estimating indirect effects and the effect of age on the relationship among variables in the model. The model's quality and fitness were assessed, and the quality criteria are presented in Table 5.

Table 5. Quality Criteria of the Model

Criterion	Saturated model	Estimated model
SRMR	0.077	0.087
d_ULS	1.256	1.596
d_G	0.419	0.468
Chi-square	464.510	494.818
NFI	0.698	0.679

The quality or fit indexes of the model are SRMR = 0.077, Exact fit criteria d_ULS = 1.256 and d_G=0.419, NFI=0.698, Chi²= 464.510. For a model to be considered fit, the values of SRMR < 0.08 and NFI > 0.90 are recommended.⁶⁹ The value of SRMR in the

⁶⁸ Hair, J. F., Ringle, C. M. and Sarstedt, M. PLS-SEM: "Indeed a silver bullet." *Journal of Marketing Theory and Practice* 19, no. 2 (2011): 139-152. <https://doi.org/10.2753/MTP1069-6679190202>.

⁶⁹ Byrne, B. M. *Structural equation modeling with EQS: Basic concepts, applications, and*

model is less than 0.08, which indicates that the model is fit, and the NFI = 0.698 indicates that the model accounts for approximately 70.0% of the total variance in the model. Therefore, the model is fit to explain variances in the hypothesized relationship.

Hypothesis 1: Higher education students' characteristics do not directly affect their intention to use AI.

Table 6. Direct Effect of Students' Characteristics on Intention to Use AI

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
ATT -> INT	0.338	0.335	0.094	3.595	0.000
Age -> INT	0.028	0.030	0.057	0.492	0.623
CON -> ATT	0.705	0.709	0.043	16.331	0.000
CON -> INT	0.168	0.166	0.073	2.313	0.021
CON -> SEE	0.650	0.655	0.050	12.886	0.000
CON -> SUN	0.400	0.410	0.056	7.108	0.000
SEE -> INT	0.186	0.186	0.087	2.142	0.032
SUN -> INT	0.225	0.232	0.063	3.579	0.000

The result shows that the direct effects of variables in the model are significant. The direct effect measured in a unit standard deviation change shows that for a unit standard deviation change in ATT, there is a corresponding 0.094 change in students' intention to use AI ($\beta = 0.094$, $t = 3.595$, $p < 0.05$). This result is similar to that of other variables, including CON ($\beta = 0.073$, $t = 2.313$, $p < 0.05$), SEE ($\beta = 0.087$, $t = 2.142$, $p < 0.05$), and SUN ($\beta = 0.063$, $t = 3.579$, $p < 0.05$). However, they reveal that age does not significantly affect students' intention to learn using AI ($\beta = 0.057$, $t = 0.492$, $p > 0.05$). This shows that individual students, irrespective of age, could decide to learn or not learn using AI.

Hypothesis 2: Higher education students' characteristics do not significantly mediate the intention to use AI.

Table 7. Indirect Effect of Students' Characteristics on Intention to Use AI

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
CON -> SEE -> INT	0.121	0.121	0.058	2.087	0.037
CON -> ATT -> INT	0.238	0.238	0.069	3.470	0.001
CON -> SUN -> INT	0.090	0.095	0.029	3.078	0.002

Table 7 presents the mediating effects of SEE, ATT, and SUN on the relationship between CON and students' intention (INT) to learn using AI. The result reveals that all the mediators significantly mediate the relationship between CON and INT. It could be observed that ATT is a relatively strong mediator ($\beta = 0.069$, 3.470, $p < 0.05$) among SEE

($\beta=0.058$, $t=2.08$, $p<0.05$), SUN ($\beta=0.029$, $t=3.078$, $p<0.05$) and ATT.

Hypothesis 3: Higher education students' age has no significant moderating effects on intention to use AI.

Table 8. Moderating Effect of Students' Age on Intention to Use AI

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Age x SUN -> INT	-0.106	-0.099	0.061	1.751	0.080
Age x SEE -> INT	-0.013	-0.015	0.091	0.143	0.886
Age x CON -> INT	0.032	0.039	0.090	0.355	0.723
Age x ATT -> INT	0.037	0.019	0.128	0.292	0.770

The result in Table 8 shows the moderating effect of age on the relationship between SUN, SEE, ATT, and INT. The result reveals that age could not significantly moderate the relationship between students' characteristics and the intention to use AI. The result reveals further that the moderating effect of age on the relationship between SUN and INT ($\beta=0.06$, $t=1.751$, $p>0.05$), SEE, and INT ($\beta=0.091$, $t=0.143$, $p>0.05$) is negative. While the moderating effect of age on the relationship between CON and INT ($\beta=0.090$, $t=0.355$, $p>0.05$) and ATT and INT ($\beta=0.128$, $t=0.292$, $p>0.05$) is positive. This implies that age could negatively affect the intention of individuals who believe in and are efficacious in learning using AI. In contrast, age could positively influence an individual's intention, attitude, and confidence in learning using AI.

Discussion

A step towards ensuring AI adoption in schools involves identifying undergraduate students' intentions to engage in AI-based learning. Understanding undergraduate students' readiness and intentions toward AI in learning and solving academic problems cannot be overstated. Artificial Intelligence (AI) classroom interactions could be made more effective by this factor. The present study did not find existing studies that specifically investigate undergraduate students' readiness and intention to use AI. This study contributes to the literature on the factors that affect undergraduate students' readiness and behavioral intentions regarding AI-based learning. The variables identified in this study that help understand undergraduate students' readiness and intention toward AI learning include confidence in learning using AI, attitudes towards learning using AI, self-efficacy to learn using AI, and intention to learn using AI.

The moderation and mediation effects in the study were established through the

assessment of SEMs, as indicated by Jaafar et al.⁷⁰ and Punshon et al.⁷¹ These studies highlight the use of SEM to disintegrate paths into direct and indirect impacts, allowing assessment of the moderation and mediation effects within the model. In addition, the significance of age as a moderator in the model emphasises the importance of considering age effects on the relationships among the variables.⁷² Overall, using SEM and related techniques enabled the thorough examination of moderation and mediation effects, contributing to a nuanced understanding of the relationships among variables in the study.

The result shows that the direct effects of variables in the model are significant and consistent with previous findings. There has been considerable interest in the characteristics of higher education students when it comes to their intentions to use AI. Several studies have explored the factors influencing students' intentions to engage with AI. Chai et al.⁷³ examined Chinese secondary school students' intention to learn using AI and found associations with relevant psychological factors. Among prospective physicians, a study that investigated their intention to use AI revealed strong beliefs in AI's role as a prerequisite.⁷⁴

The perceived usefulness of technology has been consistently identified as a critical factor affecting user intentions.⁷⁵ In addition, the influence of subjective norms and external expectations on the intention to use AI is insignificant.⁷⁶ Furthermore, educational support's role in shaping students' intentions has been highlighted, with university education support having a direct, positive effect on behavioral intentions.⁷⁷ Moreover, the lack of empirical studies and the need for innovative and meaningful

⁷⁰ Jaafar, M., Rasoolimanesh, S. M. and Ismail, S. "Perceived sociocultural impacts of tourism and community participation: A case study of Langkawi Island." *Tourism and Hospitality Research* 17, no. 2 (2017): 123–134. <https://doi.org/10.1177/1467358415610373>.

⁷¹ Punshon, T., Li, Z., Marsit, C. J., Jackson, B. P., Baker, E. R. and Karagas, M. R. "Placental metal concentrations in relation to maternal and infant toenails in a U.S. cohort." *Environmental Science & Technology* 50, no. 3 (2016): 1587–1594. <https://doi.org/10.1021/acs.est.5b05316>.

⁷² Lin, X. and Powell, S. R. "The roles of initial mathematics, reading, and cognitive skills in subsequent mathematics performance: A meta-analytic structural equation modeling approach." *Review of Educational Research* 92, no. 2 (2022): 288–325. <https://doi.org/10.3102/00346543211054576>.

⁷³ Chai, Lin, Jong, Dai, Chiu, and Huang, "Factors influencing students' behavioral intention to continue artificial intelligence learning," 147–150.

⁷⁴ Wagner, Raymond, and Paré, "Understanding prospective physicians' intention to use artificial intelligence in their future medical practice: Configurational analysis," e45631.

⁷⁵ Gado, Kempen, Lingelbach, and Bipp, "Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence?," 37–56.

⁷⁶ Ma, W. W., Andersson, R. and Streith, K. "Examining user acceptance of computer technology: An empirical study of student teachers." *Journal of Computer Assisted Learning* 21, no. 6 (2005): 387–395. <https://doi.org/10.1111/j.1365-2729.2005.00145.x>.

⁷⁷ Elshaer, I. A. and Sobaih, A. E. E. "Antecedents of risky financial investment intention among higher education students: A mediating moderating model using structural equation modeling." *Mathematics* 11, no. 42 (2023): 353. <https://doi.org/10.3390/math11020353>.

research into AI applications in higher education have been emphasised.⁷⁸

Norms and attitudes shape individuals' intentions to use AI. Studies have examined the complex interplay between attitudes, subjective norms, and intentions to use AI. Venkatesh and Davis⁷⁹ examined the TAM and concluded that attitudes significantly impact individuals' readiness to engage with technology. This highlights the importance of establishing a positive attitude toward technology to encourage its adoption. In the context of AI, positive attitudes toward its capabilities, benefits, and ease of use can lead to higher intentions to use AI systems. The relationship between attitudes and intentions is further mediated by subjective norms, which reflect perceived social pressures to engage in a particular behavior. It may strengthen an individual's intention to adopt AI technologies if they perceive that their friends and colleagues support its use. A positive attitude toward AI and supportive subjective norms may boost the use of AI technologies. Further, Cheng⁸⁰ noted that subjective norms significantly influence an individual's decision to adopt a new technology.

Conclusion

The study sheds light on higher education students' intentions to engage in AI learning. Due to the rapid growth of AI and its integration into education, it is imperative to have a comprehensive understanding of the factors that influence students' readiness and behavior. The findings underscore the significance of several key variables, including confidence in learning using AI, attitudes toward using AI, self-efficacy in learning using AI, and intention to learn using AI. The study's results affirm the substantial direct effects of these variables on students' intentions to use AI. The role of confidence, attitudes, and self-efficacy in students' AI learning decisions cannot be overstated. The study also reveals the mediating effects of these variables, indicating their interconnectedness in influencing students' intentions.

Moreover, the research addresses the potential moderating effect of age on the relationship between students' characteristics and AI learning intentions. While age does not significantly impact students' overall intentions, its nuanced influence is evident in specific relationships within the model. The study emphasises the need to consider age in understanding students' AI education engagement dynamics. Addressing the factors identified, including confidence, attitudes, self-efficacy and age-related considerations

⁷⁸ Zawacki-Richter, Marín, Bond, and Gouverneur, "Systematic review of research on artificial intelligence applications in higher education – where are the educators?," 39.

⁷⁹ Venkatesh and Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," 186–204.

⁸⁰ Cheng, E. W. L. "Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM)." *Educational Technology Research and Development* 67, no. 1 (2019): 21–37. <https://doi.org/10.1007/s11423-018-9598-6>.

becomes paramount as AI transforms global education. The study provides valuable insights for educators, policymakers, and researchers aiming to enhance AI integration into higher education, ensuring a more inclusive and effective learning environment. The findings contribute to the evolving landscape of AI in education, emphasising the importance of tailored approaches to cater to students' diverse characteristics and readiness. Acknowledging and addressing these factors will foster a positive and engaging educational experience for students as they navigate the transformative journey of AI in learning.

Considering the study's extensive findings on undergraduate students' intentions to engage in AI learning, several recommendations emerged to enhance AI integration into higher education. These suggestions address the diverse factors influencing students' readiness and intentions regarding AI in education and promoting a more inclusive and effective learning environment.

Firstly, educational institutions should consider tailoring their AI programs to accommodate students' varied characteristics, including confidence levels, attitudes, and self-efficacy. By customizing learning experiences, institutions can better cater to students' diverse readiness levels. Efforts should be directed toward empowering students' confidence in learning using AI through practical initiatives such as workshops, real-world projects, and hands-on experiences. These activities can provide students with a supportive and encouraging environment to apply AI concepts. Promoting positive attitudes toward AI is crucial. Awareness campaigns and educational initiatives can highlight AI's practical benefits and real-world applications, showcasing its potential contributions to societal advancements and individual career growth. Support systems should be implemented to enhance students' self-efficacy in AI learning.

Mentorship programs, online forums, and peer-to-peer collaboration platforms can be valuable resources for students seeking guidance and building confidence in navigating AI technologies. Recognising the nuanced impact of age on students' intentions, institutions should implement age-responsive approaches that consider diverse learning preferences and expectations across different age groups. Continuous research is essential to stay informed about evolving trends and preferences in AI education. Institutions should adapt their programs based on emerging technologies and student feedback, ensuring educational offerings remain relevant and engaging. Integrating discussions about ethical considerations related to AI into educational curricula is vital. Equipping students with knowledge of ethical issues concerning AI applications fosters the responsible and conscientious use of these technologies.

The study offers insights into undergraduate students' intentions to engage in AI learning. However, it is critical to acknowledge several limitations that may impact the interpretation and applicability of the findings. It is important to note that the generalizability of the study is constrained, as it specifically focused on higher education students in Nigeria. Attitudes toward AI may differ depending on geographic location and

cultural context. In addition, convenience sampling and online surveys introduce sampling bias. This approach may exclude individuals without internet access or those unfamiliar with online platforms, affecting the representation of diverse demographics.

Self-reported responses introduce the possibility of self-reporting bias, where participants may provide socially desirable answers or misrepresent their attitudes toward AI-based learning. The study focused on confidence, attitudes, self-efficacy, and age variables. Other influential factors like socioeconomic background, prior exposure to AI, or individual learning styles were not explored.

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