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A cross-country analysis of self-determination and continuance use intention of AI tools in business education: Does instructor support matter?

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ABSTRACT

This study builds on the recent interest in AI adoption research in academic settings by highlighting the need for culturally sensitive AI educational tools. The study achieved this by demonstrating how cultural differences shape students' motivation and AI use. This study adopts a cross-country comparative analytical approach to explore postgraduate students' motivation to continue using AI tools in the context of higher education. The study developed a theoretical model based on Self-Determination Theory (SDT) and Expectation Disconfirmation Theory (EDT) to explore how perceived competence, perceived relatedness and perceived autonomy influence the continuance use intention of AI tools in two culturally unique higher education contexts – United Kingdom and Nigeria. The study also investigates how instructor support, AI anxiety and Trust in AI moderate the relationship between self-determination and AI continuance use intention of students. The data for this study was collected using Qualtrics online survey to generate responses from postgraduate students in the UK and Nigerian HEIs contexts. The questionnaire was designed using validated existing scales. Overall, 245 and 214 valid responses were received from Nigeria and UK postgraduate students respectively. The data was analysed using Structural Equation Modelling. The findings show that perceived relatedness and perceived autonomy are important predictors of AI tools continuance use intention in both countries. The findings reveal the role of cultural differences in AI use and the relative importance of relatedness and autonomy. The results also demonstrate that instructor support plays a fundamental role in AI use. The perceived impact of AI anxiety and trust in AI on competence, relatedness and autonomy vary between the different contexts. The findings emphasise the need for culturally adaptable AI systems capable of prioritizing either collaborative or individual characteristics based on the cultural setting. The findings provide useful insights for institutions and technology firms who are interested in developing globally acceptable AI tools for educational use.

1. Introduction

Artificial intelligence (AI) is changing the landscape of higher education (HE) in unprecedented ways (Crompton and Burke 2023). Since the emergence of General Language Processing and other AI tools, several studies have explored their impact on educational outcomes (Cheah, Lu, & Kim, 2025; Budhathoki et al., 2024). Previous studies have suggested that AI tools like ChatGPT only address Bloom's lower-level skills and therefore unable to compare to humans in addressing higher order skills such as evaluating and creating (Elim 2024; Han & Wang, 2024). Meanwhile, other studies have also suggested that AI tools hallucinate and may be unsuitable for academic purposes (Budhathoki et al., 2024; Foroughi et al., 2023). Despite these criticisms, recent studies have described the application of AI tools in education as the new normal (Budhathoki et al., 2024). Chiu (2024) and Fan and Suh (2014) have found that the output generated by the AI tools depends largely on the user's proficiency, the prompts used and the capability. This means that the user's self-determination, which describes an individual's ability to execute a task successfully and independently, can influence the outcome generated from AI tools (Chiu, 2024; Ernst, 2019). Again, when users explore these AI tools, they compare the performance against their initial expectations. When the actual performance of the AI tools exceeds expectations, the tendency to continue using the tools will be higher (Fan & Suh, 2014).

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While recent studies such as Agyare et al. (2025) have examined cultural variations in AI adoption using Technology Acceptance Model, very few studies have examined how self-determination, trust and instructor support interact with cultural differences to shape the intention to continue using AI tools. Similarly, Annamalai et al. (2025) examined the use of ChatGPT in higher education and offered very useful insights, however, the findings explore only students studying English as a Foreign Language and English as a Second Language within a single context. Mustofa et al. (2025) specifically advocate for further study to examine the influence of contextual factors, including the role of instructors and institutional constraints, and trust in AI systems. Moreover, prior research has predominantly focused on undergraduate students, leaving a gap in understanding how postgraduate students, who face distinct research challenges, engage with AI tools across different contexts (Herath, et al., 2025). This study addresses these gaps by integrating Self Determination Theory (SDT) and Expectation Disconfirmation Theory (EDT) to explore cross-cultural differences in AI tools adoption, offering fresh insights into how motivation, trust, and anxiety interact to influence AI continued use in the context of Higher Educational Institutions (HEIs). Cultural differences in education, such as instructor-student relationship, digital infrastructure and trust in technology, shape students' engagement with AI tools. In Nigeria, where hierarchical instructor-student relationships are common, instructor support may play a stronger role in AI tool adoption compared to the UK, where students are expected to be more autonomous. In addition, differences in uncertainty avoidance may influence AI-related anxiety and trust in AI tools. By exploring these dynamics, this study provides deeper insights into how culture interacts with AI adoption in higher education.

Previous studies have demonstrated that the decision to continue using AI tools could be influenced by anxiety, trust, and instructor support (Schiavo et al., 2024). Budhathoki et al. (2024) used a cross-country analysis to report that users experience different kinds of anxiety when using AI tools. These can range from privacy anxiety, job-replacement anxiety, loss of information anxiety and issues around ethics (Akgun and Greenhow 2022). Also, the intention to keep using AI tools could depend on the user's trust level (Krüger & Wilson, 2023). If the trust is high, the chance of continuous use is high and vice-versa. Similarly, instructors can shape student beliefs and offer support in ways that promote ethical use, especially in an academic context (Felix 2021). According to Mimirinis et al. (2024) culture can influence how students perceive support from instructors. Despite increased interest in the adoption of AI tools among students (Budhathoki et al., 2024; Foroughi et al., 2023; Suseno et al., 2022), studies have not explored the relationship between self-determination factors and continuance use intention of AI tools among postgraduate students in Higher Educational Institutions (HEIs) from a cross-cultural perspective. More so, considering that Scholes et al. (2024) note students' mistrust on the internet, previous studies have not adequately examined how trust in AI and AI anxiety affect students' self-determination and continuance use intention of AI tools in HEIs. Thirdly, previous studies have not adequately examined how instructor support can influence the ethical use of AI tools in the context of HE.

Graduate students, unlike undergraduates, face unique academic difficulties mainly due to their inexperience in undertaking scientific research, which may turn them towards AI tools (Han & Wang, 2024). This study therefore applies SDT and EDT to investigate mechanisms that inspire postgraduate students' continued usage of AI tools. While previous studies have explored the role of SDT and EDT in various contexts, their combined application in cross-cultural contexts has not received adequate attention, particularly as it relates to AI adoption and continuance use intention among graduate students in higher education. Furthermore, previous studies have not adequately explored the mediating role of instructor support and the moderating roles of AI anxiety and trust in AI. This study contributes to SDT and EDT by exploring their applicability in cross-cultural AI adoption among postgraduate students. This study extends SDT by examining how instructor support influences self-determination in AI use across different cultural settings. Additionally, this study expands on EDT by introducing trust in AI and AI anxiety as moderating factors, providing a more nuanced understanding of AI continuance use intention across cultural contexts. Specifically, this study focuses on AI-driven research and writing tools, including ChatGPT, Grammarly, Elicit and paraphrasing tools like Quillbot and Wordtune, which are commonly used by postgraduate students for academic writing, literature reviews and critical analysis. Unlike general-purpose AI tools, these tools specifically support knowledge construction and research, making them relevant to understanding how postgraduate students integrate AI into their academic workflows. Thus, the primary research question motivating this study is: *how do self-determination, instructor* support*, AI trust, and AI-related anxiety impact postgraduate students' desire to continue using AI-assisted academic tools across diverse cultural contexts?*

Understanding how cultural differences, motivation, and trust affect AI adoption is essential for both technology companies and educational institutions as AI becomes more and more incorporated into higher education. This study offers important insights for developing culturally adaptive AI tools, improving instructor support strategies, and guiding policies that promote ethical and efficient AI use in academia by analysing the motivation of postgraduate students in Nigeria and the UK. This study makes four key contributions. First, by examining the applicability of SDT and EDT in the context of postgraduate students' AI usage, this study closes the gap between studies on AI adoption and continuation use intention across different cultural contexts. Second, the study examines the critical impact that instructor support plays in influencing students' self-determination and desire to continue using AI tools, since instructors can affect students' motivation and ongoing engagement with these tools. Thirdly, the study provides insight into moderators that might influence students' impressions of AI technologies, such as anxiety and trust in AI. Lastly, this study compares postgraduate students' perspectives in Nigeria and the UK, thereby making contributions across cultural boundaries. The findings expand on the study of Budhathoki et al. (2024), which indicated that contextual factors play a vital role in determining AI usage. The findings will advance theory and inform instructional practices and educational policies related to the integration and long-term use of AI tools in academic settings, considering the ways that cultural differences, technological infrastructure, and educational systems may influence students' attitudes and behaviours towards AI tools.

The remainder of the paper is organised as follows: Section 2 presents the theoretical framework and the study hypotheses. Section 3 explains the methodology, while the remainder of the paper articulates the results, discussion, and implications of the study findings.

2. Literature review and hypotheses development

2.1. Cultural differences in AI adoption

As technology progresses swiftly, AI has become a transformational force revolutionising several areas, including higher education (Agyare et al., 2025; Umutlu & Gursoy, 2022) (See Fig. 1). Universities are using AI's capabilities for effective teaching, improving learning outcomes, personalising student experiences, automating administrative functions, and optimising resource distribution (Agyare et al., 2025; Annamalai et al., 2025; Saihi et al., 2024). Integrating AI into intricate organisational environments has unique problems, including institutional preparedness, leadership endorsement, ethical implications, and the possible effects on faculty responsibilities and student engagement. Previous research on AI utilisation in higher education across various cultural contexts repeatedly demonstrates that cultural factors influence the adoption, perception, and integration of AI technologies (Camacho-Zuñiga, 2024; Sharma et al., 2024). In Western institutions like the UK where individualism is high, students tend to have greater autonomy in technology use, experimenting with AI-driven resources

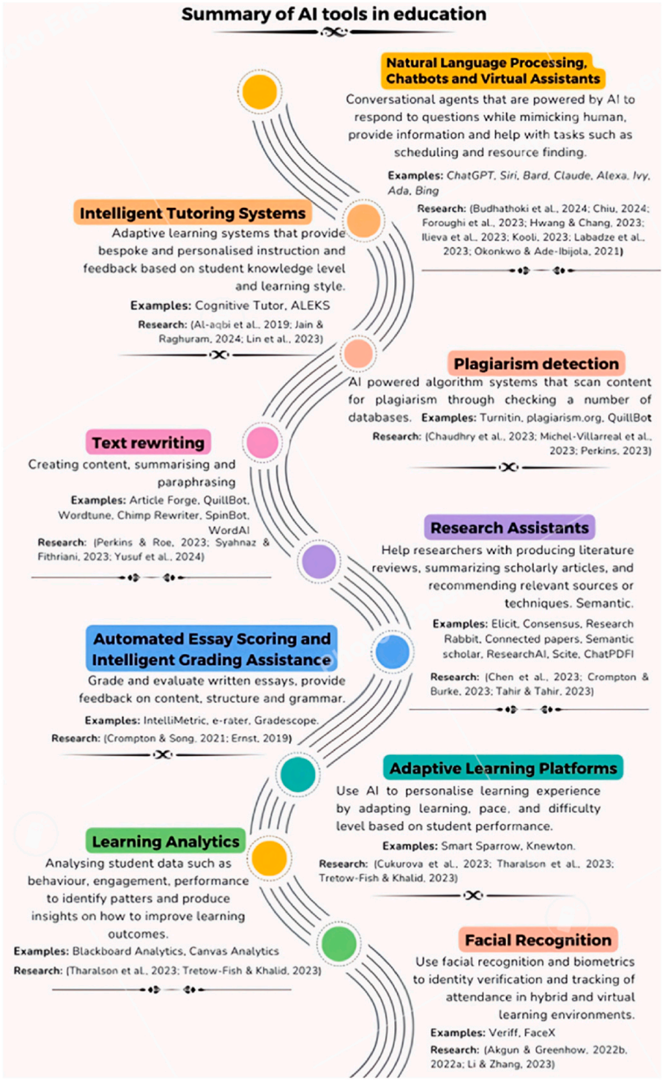


Fig. 1. Summary of AI tools used in education.

and exhibiting independent learning behaviour (Huang et al., 2023; Lin & Chen, 2024; McGrath et al., 2023). On the other hand, in collectivist cultures like Nigeria, there is greater reliance on instructor and peer guidance in adopting new technologies (Sanusi et al., 2022).

Moreover, technology in such contexts is influenced by communal learning traditions, socioeconomic barriers and institutional support structures. (Kaya et al., 2024; Lee et al., 2024). Also, in cultures like the UK, students generally benefit from well-established digital infrastructure, including access to advanced e-learning platforms, high-speed internet and institutional support, whereas students in countries like Nigeria face challenges related to limited internet access, high-data costs and inconsistent power supply, which hinder seamless engagement with educational technologies (Agbarakwe & Adedeji, 2024; Eze & Onah, 2024). These infrastructural disparities also contribute to differences in how students from both regions perceive and use technology for learning (Erdmann & Toro-Dupouy, 2025).

In the same vein, while institutions in the UK emphasise student-centred learning, which promotes the use of technology for independent research, collaboration and self-paced learning, contexts like Nigeria have stronger reliance on traditional lecture-based teaching methods where technology is often integrated as a supplementary tool, rather than as a primary mode of instruction (Agbarakwe & Adedeji, 2024; Essien et al., 2024). Also, cultural factors such as respect for authority and hierarchical structures in the Nigerian academic context may influence the willingness of students to engage in technology-driven, self-directed learning (Agbarakwe & Adedeji, 2024; Bali et al., 2024). Other studies have also argued that trust in technologies such as AI varies across cultures and can affect students' willingness to adopt and use AI. In countries where individualism is high, students express greater autonomy, experimenting with AI-driven resources.

However, in contexts with collectivist cultural norms, reliance on external support is higher. More so, in countries like the UK, institutional safeguards, AI policies and data privacy regulations increase trust in AI (Huang et al., 2023; Jin et al., 2025). Conversely, countries such as Nigeria express scepticism due to concerns about data privacy, reliability and perceived bias in AI systems (Essien et al., 2024; Eze & Onah, 2024). This distrust is exacerbated by lower exposure to AI in the everyday learning environment and infrastructural challenges (Agbarakwe & Adedeji, 2024; Eze & Onah, 2024; Li & Huang, 2020). Similarly, how instructors support learning differs across cultures. In countries such as the UK, institutions encourage self-directed learning by giving students the flexibility to integrate AI tools based on personal preferences (Huang et al., 2023). However, in other contexts like Nigeria, students rely on institutional mandates to validate technology use, which leads to a more structured adoption process (Bali et al., 2024; Essien et al., 2024). These contrasting cultural differences not only impact the style and rate of technology adoption, but they also highlight the role of institutional culture in shaping engagement with technology.

Although disparities in digital access persist across culture, recent findings suggest that globalisation and increased exposure to international digital learning standards are gradually narrowing these challenges. Collaborative AI tools, hybrid learning modules and collaborative online learning environments are bridging the gaps across contexts. While existing research has explored cultural differences in technology adoption, there is a lack of studies that investigate how social determination factors (such as autonomy, competence and relatedness) influence continued use of AI technology. Moreover, the increasing integration of AI in education introduces psychological barriers including AI anxiety (Li & Huang, 2020; Wang & Wang, 2022), which has been underexplored particularly in non-western contexts. Likewise, trust in different AI technologies in educational settings across contexts has been under-researched. Considering that AI-powered tools such as Chatbots, word rewriting tools and language models such as ChatGPT and Bing are becoming mainstream in HEIs, it is important to explore how variations in these factors influence students' learning experiences across different contexts (Budhathoki et al., 2024; Foroughi et al., 2023).

The utilisation of AI systems in education has brought about a paradigm shift in the way students obtain information and gain knowledge (Brill et al., 2019; Raffaghelli et al., 2022). This study applies SDT and EDT to understand the factors shaping students' AI technology continuance use intentions. SDT is a widely recognised meta-theory that explores human motivation and personality in social environments (Ryan & Deci, 2000; Deci & Richard, 2012). Thus, SDT proposes that individuals engage in activities such as use of AI tools without being swayed or driven by other stimuli (Chiu, 2024; Ng et al., 2012). According to SDT, every individual's determination to engage with AI technology is characterised by three essential psychological needs: autonomy, competence, and relatedness (Xia, Chiu, and Chai, 2023).

Autonomy describes the perception of having the liberty to make decisions and engage in independent behaviour, through individual preferences and values (Su and Chen 2022). Competence is defined as possessing a high level of ability and expertise, as well as a strong motivation to be productive and succeed in completing tasks (Xia et al., 2022). Relatedness explores an individual's natural tendency to form connections and cultivate a sense of belonging (Roca and Gagné 2008). SDT also explains how societal and cultural influences can either enable or hinder individuals' perception of personal control and drive, as well as their overall state of wellbeing and performance (Chiu, 2024). Researchers have applied SDT to examine human motivation in diverse settings, including chatbots (Xia et al., 2023a), e-learning (Sørebø et al., 2009), AI education (Chiu, 2024; Xia et al., 2022), ChatGPT (Chiu, 2024), and automated systems (Ernst, 2019). In this study, SDT is applied to understand how the psychological self-determination need for autonomy, competence and relatedness among postgraduate students influences their AI tools continuous use intention. The SDT thesis as applied in this study suggests that when students perceive that AI technologies and tools support their autonomy, enhance their competence, and facilitate meaningful connections with peers and instructors, their self-determination and intrinsic motivation to continue using AI tools may increase (Ryan & Deci, 2000; Su and Chen 2022; Sørebø et al., 2009).

On the other hand, EDT argues that individuals form prior expectations about a situation, or stimuli based on various information sources, including social influences, prior experiences, and cultural norms (Carraher-Wolverton, 2022; Carraher-Wolverton & Hirschheim, 2023). EDT, derived from customer satisfaction research, suggests that prior expectations before using a technology such as AI act as a benchmark upon which the individuals assess their actual experiences (Bhattacherjee, 2001; Oliver et al., 1994). Thus, individuals form and adjust their expectations based on how their actual experiences match their initial expectations (Nooij et al., 2022; Sinha et al., 2020). Satisfaction is thus, achieved when the performance surpasses expectations, resulting in positive disconfirmation (Carraher-Wolverton & Hirschheim, 2023). Conversely, if the performance is not up to expectations, it leads to negative disconfirmation, which ultimately causes unhappiness and discontinuation (Carraher-Wolverton, 2022).

EDT has been applied to a variety of scenarios in HE. For instance, EDT has been applied to study students' illusion of control and its impact on unrealistic optimism (Luna-Cortes, 2024), why students switch to disruptive technology (Fan & Suh, 2014), students' perception of educational services (Arena et al., 2010) and the role of AI in HE, including AI instrumentality (Raffaghelli et al., 2022), the role of voice assistants such as Siri and Alexa (Brill et al., 2019), and the intention to use ChatGPT for educational purposes (Foroughi et al., 2023). In this study, EDT has been used to investigate how postgraduate students in HE perceive the benefits of AI technology in education contexts and how those perceptions affect such students' post-adoption satisfaction levels and continued use of AI technology for academic purposes. EDT has been applied in this study because it asserts that the level of satisfaction and continuance use intention of AI tools in the context of HE depends on whether the performance meets, surpasses, or falls below the expectations of the students who use it (Lankton, McKnight, and Thatcher, 2014; Nooij et al., 2022). Hence, there will be positive disconfirmation when AI tools perform better than expected, which may lead to satisfaction and increased continuance use intention by students or a negative disconfirmation when there is lower satisfaction with AI tools, which may lead to lower satisfaction levels and reduced continuance use intention among students.

While previous studies have extensively explored the role of EDT and SDT in various educational contexts, there is limited attention exploring their applicability in the context of AI adoption and continued use intention in HE, specifically among postgraduate students from different cultures. By integrating SDT and EDT, this study proposes a comprehensive theoretical framework to explore the factors influencing the continuance use intention of AI technologies. While SDT emphasises the importance of fulfilling psychological needs for self-determination and intrinsic motivation (Chiu, 2024; Xia et al., 2022), EDT will provide insights into the role of expectation disconfirmation and satisfaction in AI tools continuance use intention (Luna-Cortes, 2024).

2.2. *Self-determination and continuance use intention*

Perceived cognitive competence is a crucial element for students struggling with inherently complicated AI systems (Sanusi et al., 2022). This study posits that enhancing learners' cognitive capabilities may influence their competence in using AI technologies, including ChatGPT, Elicit, and word rewriters, for academic purposes. According to SDT, students are driven to utilise technologies that fulfil their psychological demands for competence, relatedness, and autonomy. The psychological demand for competence pertains to the capacity to proficiently interact with one's environment (He & Li, 2023). Yoon and Rolland (2012) assert that the urge for competence relates to individuals' want to engage with their surroundings proficiently, achieve favourable results, and evade unfavourable occurrences. Students whose competency requirements are satisfied exhibit confidence in their successful utilisation of AI technologies like ChatGPT and word rewriters (Foroughi et al., 2023; He & Li, 2023; Santana-Monagas et al., 2022). Prior studies have demonstrated a favourable correlation between perceived competence and AI technologies, including ChatGPT, Elicit, and word rewriters (Foroughi et al., 2023; Zhang & Zhou, 2023). Rahi et al. (2022) found that an individual's perception of their ability positively influences their readiness to adopt and utilise AI technology. This research (See Fig. 2) posits that students in the UK and Nigeria, driven by perceived competence, would exhibit a propensity to persist in using AI technologies for academic endeavours. This article proposes that.

H1. Perceived competence of postgraduate students positively influences the continuous use intention of AI tools.

Despite the application and promise of SDT in educational settings, a notable gap persists in the research regarding its application in AI across various contexts. Currently, there is a lack of empirical data directly linking the fulfilment of psychological needs, as defined by SDT, to certain facets of AI usage among students from diverse cultural backgrounds. While SDT is extensively used to understand several dimensions of digital literacy, the relationship between learners' psychological needs satisfaction and their intention to continue using AI has been under-explored, particularly in developing countries like Nigeria. Research based on SDT shows that meeting learners' essential psychological needs, such as relatedness can significantly enhance multiple aspects of their AI usage (Wang et al., 2025). Perceived relatedness (PR) refers to the tendency to foster a deep sense of connection and attachment to others (Yoon & Rolland, 2012; Zhang & Zhou, 2023). Postgraduate students can achieve the desired interpersonal connections through the participation and support of instructors and classmates (Santana-Monagas et al., 2022). PR highlights the extent to which AI technologies are integrated into an individual's social interactions (Zhang & Zhou, 2023). He and Li (2023) found that perceived relatedness reliably predicts Chinese students' continuance use of new technology for second language acquisition. Similarly, Cortez et al. (2024) found that the perceived relationship between relatedness and the continued use of AI tools, such as ChatGPT, Elicit, and paraphrasing tools in education, greatly influences students' willingness to continue using AI as an educational resource. Therefore, the following theory has been proposed.

H2. *Relatedness of postgraduate students positively influences the continuous use intention of AI tools.*

Generative AI technology, by simulating human-like interactive communication, offers students tailored learning materials, enabling them to control their learning speed and process, so reshaping their perception of autonomous learning (Wang & Li, 2024). Wang et al. (2025) assert that students in higher education possess greater autonomy owing to diminished external supervision of their learning processes. This increased autonomy necessitated that students exercise greater control over their learning, making self-regulated learning progressively vital. This proactive strategy enables learners to efficiently manage and enhance their educational experiences, promoting increased academic success and personal development. Wang et al. (2025) recognises the possibility of using intelligent learning technology to evaluate and improve self-regulated learning. Perceived autonomy (PA) promotes the idea that an individual's activities are determined by their own free will and choice (Ryan & Deci, 2000; Deci & Richard, 2012). Rahi et al. (2022) describe PA as an individual's subjective

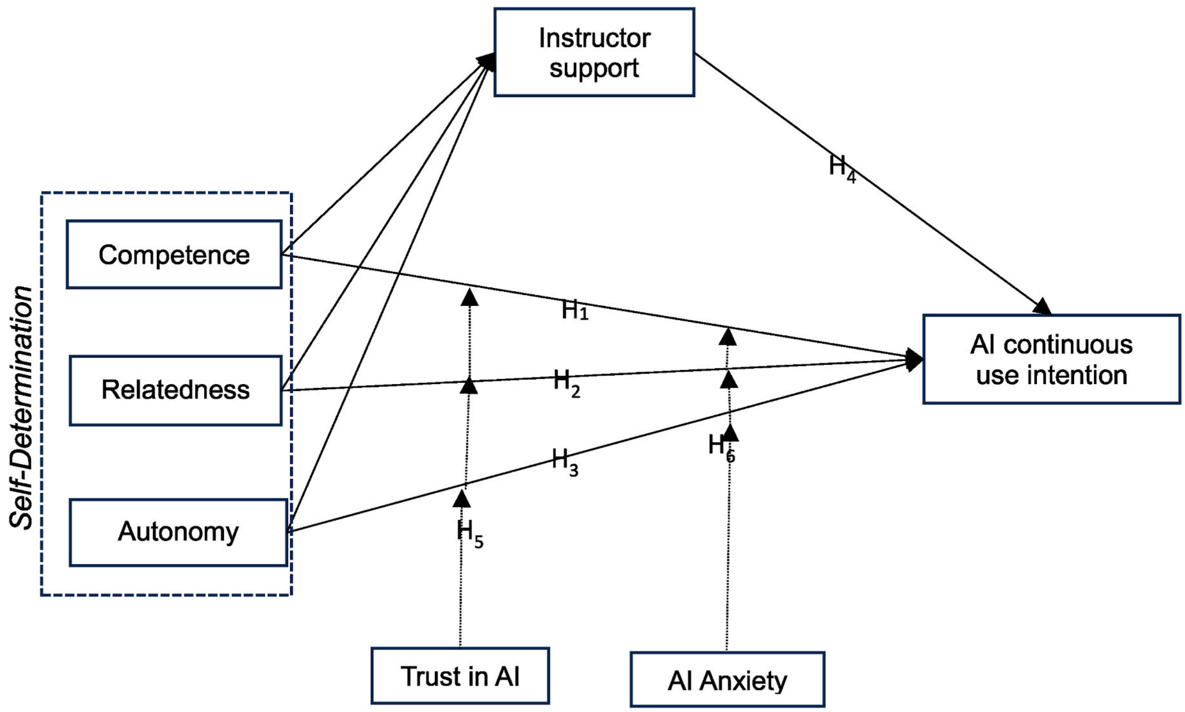


Fig. 2. Hypothesised research model.

assessment of their competence to complete a task without relying on external help. Both Santana-Monagas et al. (2022) and Ernst (2019) highlight the importance of autonomy in the use of AI tools such as ChatGPT, Elicit and word rewriters. Ernst (2019) discusses the potential of emerging AI tools such as AI research assistants and other tools to erode individuals' freedom to self-determination, whereas Santana--Monagas et al. (2022) emphasise the significance of autonomy in influencing students' interest. Zhang and Zhou (2023) further emphasise this by highlighting that autonomy is a fundamental principle of SDT when it relates to AI adoption and continued use. Santana-Monagas et al. (2022) support this idea by asserting that students' use of technology can be driven by a desire for autonomy. Thus, this study hypothesises that.

H3. *Autonomy of postgraduate students positively influences the continuous use intention of AI tools.*

2.3. The mediating role of instructor support (IS)

According to Wang and Li (2024), the effective use of generative AI technology for autonomous learning is becoming increasingly critical for university students looking to obtain skills and adapt to a rapidly changing job market. Lee et al. (2024) argue that one of the most important issues with student AI use for assessments is that educators are confronted with new challenges. These challenges include the inability to depend on current assessment processes and not understanding how to construct new assessments that can reduce students' overdependence on AI tools such as ChatGPT. As is common with new technologies, there are worries about which technology to employ, how it should be utilised, and what training and support will be provided to ensure competent responses to AI implementation (Lee et al., 2024). Previous studies have emphasized the need for further support to aid instructors in cultivating AI competencies and literacies on one hand, and the provision of tailored guidance to students on the ethical and professional use of AI tools such as ChatGPT on the other hand (Lee et al., 2024; McGrath et al., 2023).

Lee et al. (2024) note that university educators perceive AI as both a threat and an opportunity. A common issue in conversations about AI in education is the fear that AI may replace teachers. However, educators see it crucial to involve students in debates about AI since it promotes a collective analysis of AI's potential benefits and downsides. Educators contend that including students in these discussions may enhance their learning experience and empower them to employ AI ethically as a valid educational resource (Camacho-Zuñiga, 2024; Lee et al., 2024). Al-Zahrani and Alasmari (2024) underscore the role of educators in fostering positive student viewpoints and attitudes, which can help to deliver personalised learning experiences. Instructors adopt various methods to facilitate learning that align with established standards for ethical instruction (Loui, 2005). He and Li (2023) note instructor support is crucial for fostering self-determination, engagement, and self-reliance (He & Li, 2023; Loui, 2005). Previous findings show that IS can have a positive effect on students' sense of autonomy and the satisfaction associated with the use of AI tools (Han & Wang, 2024; Wang et al., 2022). According to Loui (2005) instructors can support students in adjusting to new technology by providing them with behavioural, capacity, and emotional support. Therefore, the following hypothesis is proposed.

H4. Instructor support mediates the relationship between self-determination (competence, relatedness, and autonomy) of postgraduate students' and continuous use intention of AI tools.

2.4. Moderating roles of AI anxiety and trust in AI

AI technology has presented challenges such as job displacement, privacy and transparency concerns, algorithmic biases, widening socio-economic inequalities, and unethical activities. These issues may cause disturbances that manifest as anxiety (Kaya et al., 2024; Li & Huang, 2020). AI anxiety is defined as an intense apprehension arising from concerns related to the changes induced by AI technology in personal or social situations (Schiavo et al., 2024). Wang and Wang (2022) categorised AI anxiety into four dimensions: "*job replacement anxiety*," describing fears regarding AI's adverse effects on employment; "*sociotechnical blindness*," indicating anxiety arising from a limited understanding of AI's dependence on human input; "*AI configuration anxiety*," reflecting apprehension about humanoid AI; and "*AI learning anxiety*," associated with unease regarding the adoption of AI technologies. Li and Huang (2020) included other factors such as privacy, transparency, bias, and ethics into the notion of AI anxiety. AI anxiety is an emerging concept, and there is a lack of research regarding the relationship between an individual's fear of AI and their use perceptions, as well as the interaction with other factors.

A recent study comparing the moderating role of AI anxiety on students' use behaviour in Nepal and the United Kingdom found that AI anxiety did not have a substantial influence on usage behaviour in Nepal (Budhathoki et al., 2024). Nevertheless, Budhathoki et al. (2024) found that in the UK, anxiety can influence behavioural intentions, but it did not have any influence on students' actual usage of ChatGPT. This suggests that students in the UK may feel hesitant due to anxiety, as high levels of anxiety could lead to scepticism. Nevertheless, this uncertainty may not inevitably impede its practical application, potentially due to other factors such as perceived utility and instructor support outweighing the anxiety-induced reluctance. Suseno et al. (2022) found that concerns about AI had a negative effect on people's willingness to use AI technology. Similarly, trust helps to deal with vulnerability, uncertainty, complexity, and ambiguity in circumstances that offer a threat (Choung et al., 2023a). Previous studies have not examined these factors contextually to identify their influence on students' use of AI tools in academic settings such as Nigeria. Understanding the social and psychological aspects that affect people's confidence in the relationship between humans and AI is essential to maintaining continued AI use (Krüger & Wilson, 2023). This study proposes that AI anxiety and trust moderate the relationship between self-determination of postgraduate students and AI tools continuance use intention in the UK and Nigeria (See Fig. 2). Thus, this study proposes that.

H5. Trust in AI moderates the relationship between self-determination (competence, relatedness, and autonomy) of postgraduate students' and continuous use intention of AI tools.

H5. AI Anxiety moderates the relationship between self-determination (competence, relatedness, and autonomy) of postgraduate students' and continuous use intention of AI tools.

The hypothesised research model as shown in Fig. 2 below.

3. Research method

3.1. Participants and data collection

This study collected data from postgraduate students in the UK and Nigeria using Qualtrics online survey. The data included students from Accounting, Business Management, Marketing, Entrepreneurship, Banking and Finance, Taxation and International Business. The selection of the UK and Nigeria is based on their contrasting levels of AI adoption in education. The UK, with its strong digital infrastructure and institutional AI policies, provides a setting where AI tools are already embedded in academic practices. In contrast, Nigeria, where AI adoption is still emerging due to infrastructural and institutional constraints, offers a unique comparative perspective. By exploring these two diverse contexts, this study provides insight into how different levels of technological development influence AI tools' continuance use intention among postgraduate students. The focus on postgraduate business students is due to the growing integration of AI tools in business education. AI tools are widely used for financial modelling, data analysis, strategic decision-making and literature mapping, making business students a relevant group for AI adoption in academic settings. Moreover, business programs increasingly emphasise technology-driven learning, which aligns with the research objectives of this study.

The questionnaire was presented in English. This is because English is native to UK institutions and the official language of instruction for Nigerian students. The survey was distributed to 2922 postgraduate students from Nigeria and the UK, and 495 responses were received, accounting for a response rate of 16.94 %. In total, 36 responses were invalid due to skewed or missing responses. This response rate is influenced by the targeted sample of postgraduate students who typically have demanding academic and professional commitments. Moreover, participation was restricted to students with prior experience using AI tools such as ChatGPT, Grammarly, Elicit and paraphrasing tools like Quillbot and Wordtune, ensuring that participants had sufficient familiarity with AI tools. Despite these limitations, the final dataset provides meaningful insights as it includes only students with direct engagement in AI-supported academic tasks.

Table 1 provides a summary of the demographic statistics of the respondents.

3.2. Measures

All the scales were adapted from previous studies and modified to fit the research context. The scale for self-determination was adapted from Sørebø et al. (2009). The scale was measured with three components of self-determination: PC (6-items), PR (8-items) and PA (7-items). To measure the mediator variable, IS was adapted using a 5-item scale from Hone and Ghada (2016). For the two moderating variables, AI anxiety was measured using a 9-item technology anxiety scale developed by Meuter et al. (2003) and trust in AI was measured using 4-items adapted from Choung et al. (2023b). Continuance use intention was measured using a 3-item scale adapted from Wu and Chen (2017). All the scale was anchored on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

4. Results

4.1. Measurement model

To assess the structural and measurement model, SEM technique was used. The results were analysed using IBM SPSS AMOS (v28). Table 2 presents the descriptive statistics and the Pearson's correlations between all the factors for Nigeria and UK. As shown in Table 3, all PC, PR, and PA positively correlated with continuance intention, with mean ranging from M = 5.701 to 5.856 and SD = 0.539 to 1.144. The CFA results met the threshold for acceptable model fit. Similarly, as shown in Table 2, Cronbach's α coefficients, which were used to measure the construct reliability, met the recommended threshold of $\alpha \geq .70$ (Budhathoki et al., 2024). The α for Nigeria ranged from 0.74 to 0.86 while the α for UK ranged from 0.70 to 0.87. As shown in the Appendix, composite reliability (CR), AVE and factor loadings meet the minimum acceptable thresholds. Hair, Howard, and Nitzl (2020) recommended a CR of 0.70 while Fornell and Larcker (1981) recommended a CR value of ≥0.60 and an AVE ≥0.50. The results showed that for Nigeria, CR = 0.71 to 0.94 and AVE = 0.50 to 0.70 while for UK, CR = 0.70 to 0.90 and AVE = 0.50 to 0.55. As recommended by Hair, Howard, and Nitzl (2020), the square

Table 1
Sample demographic characteristics.

Category		Nigeria		United Kingdom	
		N=245		*N=214*	
		n	%	*n*	%
Level	Master	235	95.9	207	96.7
	PhD	7	2.9	6	2.8
	Other (MBA)	3	1.2	1	0.5
AI Tools	Writing	117	47.8	106	49.5
	Paraphrasing	46	18.8	43	20.1
	Research Assistant tools	35	14.3	25	11.7
	Proofreading/Grammar	17	6.9	17	7.9
	Others	30	12.2	23	10.7
Gender	Male	136	55.5	89	41.6
	Female	109	44.4	118	55.1
	Prefer not to say	–	–	7	3.3

Table 2
Descriptive statistics, correlations, and Reliability.

		Country	α	1	2	3	4	5	6	7
Nigeria	1	Competence	0.83			.				
	2	Relatedness	0.77	0.317[a]		.				.
	3	Autonomy	0.74	0.489[a]	0.414[a]				.	
	4	Trust	0.74	0.343[a]	0.426[a]	0.410[a]		.		
	5	Anxiety	0.80	0.191[a]	0.396[a]	0.123	0.344[a]			
	6	Support	0.75	0.070	0.365[a]	0.166[a]	0.352[a]	0.626[a]		
	7	Intention	0.86	0.412[a]	0.567[a]	0.513[a]	0.489[a]	0.545[a]	0.538[a]	
	M			5.701	5.706	5.778	5.856	5.740	5.830	5.796
	SD			0.981	0.828	1.046	0.569	1.144	1.121	0.539
	Square root of AVE			0.707	0.837	0.707	0.748	0.728	0.728	0.748
UK	1	Competence	0.71							
	2	Relatedness	0.76	0.301[a]						
	3	Autonomy	0.78	0.332[a]	0.429[a]			.		
	4	Trust	0.70	0.375[a]	0.426[a]	0.596[a]				
	5	Anxiety	0.83	0.548[a]	0.325[a]	0.324[a]	0.494[a]			
	6	Support	0.77	0.680[a]	0.383[a]	0.437[a]	0.479[a]	0.792[a]		
	7	Intention	0.87	0.493[a]	0.498[a]	0.648[a]	0.612[a]	0.660[a]	0.686[a]	
	M			5.796	5.574	5.667	5.755	5.909	5.490	5.43
	SD			0.539	1.211	0.933	1.102	0.515	1.436	1.476
	Square root of AVE			0.721	0.748	0.707	0.742	0.714	0.714	0.734

[a] Correlation is significant at the 0.01 level (2-tailed).

Table 3
CFA results.

	Country	p	CMIN/DF	RMR	SRMR	GFI	NFI	TLI	CFI	RMSEA
Competence (PC)	*UK*	*.004*	*3.885*	*.027*	*.035*	*.98*	*.97*	*.90*	*.97*	*.013*
	Nigeria	*.794*	*.420*	*.008*	*.008*	*.99*	*.99*	*.99*	*.99*	*.000*
Relatedness (PR)	*UK*	*.046*	*1.745*	*.047*	*.035*	*.96*	*.96*	*.97*	*.98*	*.007*
	Nigeria	*.109*	*1.542*	*.024*	*020*	*.98*	*.98*	*.99*	*.99*	*.048*
Autonomy (PA)	*UK*	*.105*	*1.696*	*.056*	*.035*	*.98*	*.97*	*.98*	*.99*	*.056*
	Nigeria	*.038*	*2.126*	*.053*	*.039*	*.98*	*.97*	*.96*	*.98*	*.060*
Instructor support (IS)	*UK*	*.340*	*1.079*	*.020*	*.017*	*.99*	*.99*	*.97*	*.99*	*.019*
	Nigeria	*.493*	*.707*	*.010*	*.014*	*.98*	*.99*	*.99*	*.99*	*.000*
Anxiety	*UK*	*.44*	*1.597*	*.039*	*.042*	*.97*	*.94*	*.96*	*.98*	*.052*
	Nigeria	*.001*	*2.256*	*.038*	*.047*	*.96*	*.93*	*.93*	*.96*	*.054*
Trust	*UK*	*.774*	*.256*	*.008*	*.011*	*.99*	*.99*	*.98*	*.95*	*.000*
	Nigeria	*.857*	*.154*	*.005*	*.0075*	*.99*	*.99*	*.99*	*.99*	*.000*

root of the AVE for each construct exceeded the intercorrelation values (See Table 2), indicating excellent discriminant validity among variables. Harman's single-factor test was performed to check for common method bias (CMB). The results showed that the first factor accounted for approximately 30 % of the total variance, which is below the 50 % threshold, suggesting that CMB is not a major concern.

Before conducting the SEM analysis, we assess the measurement properties for each construct. Table 3 presents the goodness-of-fit indices for the models, which reveal that both models achieved an excellent overall fit. As shown in Table 3, the fit indices meet the minimum thresholds recommended in previous studies (Budhathoki et al., 2024).

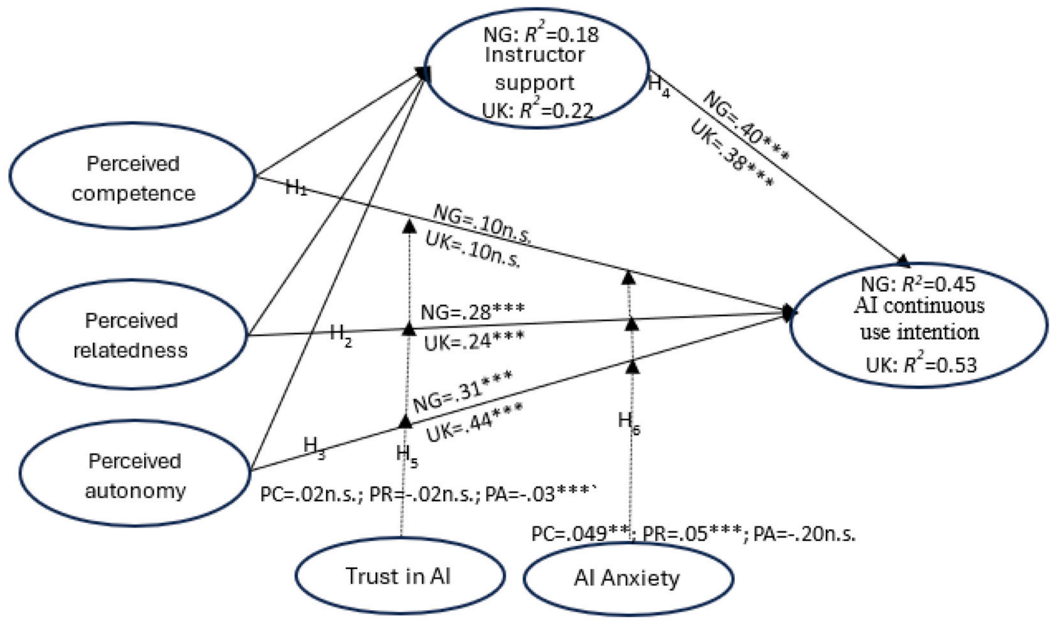
4.2. *Structural model*

A path analysis was used to assess and test the relationship among the hypothesised variables. The model was tested for UK and Nigeria (See Fig. 3). The result of the test is presented in Table 4. In the context of Nigeria, the results support H_2 and H_3 confirming that the self-determination of students has a strong influence on their continued use of AI tools for academic purposes. Although, the findings show that the relationship between competence and continued use intention of AI tools by postgraduate students is not significant ($\beta = 095$, C.R. $= 1.393$, $p > .01$), the results demonstrate that there is also a positive and significant relationship between relatedness and continued use intention ($\beta = 168$, C.R. $= 4.137$, $p < .01$). The findings show that there is a positive and significant relationship between autonomy and continued use intention ($\beta = 312$, C.R. $= 4.814$, $p < .01$). In addition, the findings show that IS in the context of Nigeria demonstrates the strongest influence on the propensity of Nigerian students to continue using AI tools for academic purposes ($\beta = 401$, C.R. $= 5.583$, $p < .01$).

As shown in Fig. 3 and Tables 4 and in the context of the UK, only two direct hypothesised relationships (H_2 and H_3) were supported. The results show that there is a positive and significant relationship between relatedness and continued use intention ($\beta = 0.244$, C.R. $= 3.788$, $p < .01$). PA of UK students demonstrated the strongest association with AI continuance use intention ($\beta = 0.444$, C.R. $= 7.163$, $p < .01$). In addition, the findings show that IS in the context of UK has a positive and significant influence on the propensity of UK students to continue using AI tools for academic purposes ($\beta = 0.383$, C.R. $= 5.509$, $p < .01$). In comparison to Nigeria, the role of IS on continuance use intention is greater when compared to the UK, even though both results emphasise the significant role of IS. Like the findings from Nigeria, the results reveal that the relationship between PC and continued use intention of AI tools by postgraduate students in the UK is not significant. ($\beta = 098$, C.R. $= 1.479$, $p > .05$). Thus, H_1 is rejected in the context of UK.

4.3. *Mediation analysis*

Mediation analysis is a statistical technique often used to explore the mechanism by which an independent variable (X) impacts a dependent variable (Y) via a mediator variable (M) (Hayes, 2009). The mediation effect of instructor support (M) on the relationship between PC, PR and PA (X) and AI continuance use intention (Y) was tested using AMOS



****p < .01, *p < .05; PC=Competence, PR=Relatedness; PA=Autonomy; CI=Continuance intention. n.s.= Not significant; NG= Nigeria= CMIN/DF = 2.462, GFI= .95 .001, CFI = .97, TLI = .96, RMSEA = .056. UK= United Kingdom; CMIN/DF: χ2 = 2.442. GFI= .93, CFI = .94, TLI = .96, RMSEA = .045*

Fig. 3. SEM path analysis results of the hypothesised model for Nigeria (n = 245) and UK (n = 214).

Table 4
Direct hypothesised path.

		Nigeria			UK		
	Path	*β*	t-value	Remark	*β*	t-value	Remark
H_1	PC ⟹CI	0.095	1.393	*Rejected*	0.098	1.479	*Rejected*
H_2	PR ⟹CI	0.282	4.137***	*Supported*	0.244	3.788***	*Supported*
H_3	PA ⟹CI	0.312	4.814***	*Supported*	0.444	7.163***	*Supported*
	IS ⟹CI	0.400	5.583***	*Supported*	0.383	5.509***	*Supported*

Notes: ***p < .01, *p < .05; PC=Competence, PR=Relatedness; PA=Autonomy; CI=Continuance intention.

v.28. The mediation was tested using a bootstrap sample of 5000 at 95 % confidence interval to increase the accuracy of the predictions (Han & Wang, 2024; Hayes, 2009). The results reveal that for Nigerian and UK students, IS partially mediates the relationship between PC, PR, PA, and AI tools continuance use intention, with Nigeria ($B = 0.17$; $p < .01$) and UK ($B = 0.14$; $p < .01$) showing a positive relationship respectively. This finding demonstrates the fundamental role of instructors in the ethical use of AI tools in the HE context.

4.4. *Moderating effects of AI anxiety and trust in AI (H_5 and H_6)*

Moderation analysis was performed to explore the potential moderating roles of AI anxiety and Trust in AI in the relationship between self-determination and continuance use intention in Nigeria and the UK. In the model combining the data from UK and Nigeria, the results reveal a mixed outcome with significant and non-significant interaction effects. Generally, AI anxiety moderates the relationship between PC and AI continuance use intention (β = 0.08; C.R. = 4.460; $p < .01$). Similarly, AI anxiety moderates the relationship between PR and AI continuance use intention (β = 0.049; C.R. = 2.501; $p < .05$), However, AI anxiety does not moderate the relationship between PA and AI continuance use intention (β = −0.020; C.R. = -1.092; $p > .05$). The results demonstrate that trust does not moderate the relationship between PC and AI continuance use intention (β = 0.02; C.R. = 1.553; $p > .05$). Likewise, trust in AI does not moderate the relationship between PR and AI continuance use intention (β = −0.012; C.R. = -0.992; $p > .05$). Interestingly, the findings show that Trust moderates the relationship between PA and AI continuance use intention (β = −0.030; C.R. = -2.911; $p < .01$).

These findings suggest that, depending on the context, AI anxiety and trust in AI play a significant role in shaping the link between self-determination and continuance use intention, highlighting the importance of considering the role of anxiety and trust in the application of AI tools in different educational contexts.

5. Discussion

The findings offer valuable insights into how students' psychological needs, expectations and contextual factors shape technology adoption and continuance use behaviour. From the perspective of SDT, satisfying students' innate psychological needs for relatedness, competence and autonomy can lead to intrinsic motivation to continue using AI tools. This study demonstrates that perceived relatedness and autonomy influence the continuance use intention of AI tools in various educational contexts, with relatedness being more influential in Nigeria and autonomy more prominent in the UK. However, the unexpected finding is that perceived competence did not significantly predict continuance use intention. This deviation from core SDT assumptions suggests that AI's user-friendly nature minimises the need for high competence, shifting the emphasis to social and contextual motivations. These findings align with constructivist learning theories, particularly Vygotsky's socio-cultural theory which emphasises the role of social interactions in learning (Zajda & Zajda, 2021, pp. 35–50).

The results suggest that students who experience a sense of closeness and connection with peers and instructors are more likely to continue utilising AI technologies. This aligns with previous findings that students with a sense of social inclusion and community are more likely to persist in employing AI technology (Mahmoud, 2024; Santana-Monagas et al., 2022; Xia et al., 2022, 2023). A robust sense of autonomy signifies that students have considerable agency to oversee their learning processes and engage with AI technology autonomously (Ernst, 2019; Santana--Monagas et al., 2022; Zhang & Zhou, 2023). SDT posits that satisfying students' fundamental psychological needs for competence, relatedness, and autonomy can enhance intrinsic motivation (Ryan & Deci, 2000). This study confirms previous findings, indicating that felt relatedness and perceived autonomy influence the intention to persist in using AI technology within educational contexts. Thus, postgraduate students who experience relatedness and autonomy while using AI technologies are more likely to persist in their usage (Santana-Monagas et al., 2022; Zhang & Zhou, 2023). Surprisingly and rather counterintuitively, perceived competence does not significantly predict continuance use intention in both countries, which contradicts the core assumptions of SDT. One plausible explanation for this finding could be that, since AI tools are ubiquitous and user-friendly, the perceived need for high competence levels among students is reduced.

The study illustrates the need for fostering autonomy and relatedness through AI-enhanced learning. The strong emphasis on relatedness in the context of Nigeria suggests that AI tools should be integrated into collaborative learning models that encourage peer interaction and knowledge sharing. Conversely, in individualistic cultures such as the UK, AI tools should be designed to support personalised learning experiences, thereby fostering autonomy and self-regulated learning. Thus, given that autonomy strongly predicts AI use in the UK, institutions should integrate AI tools that support self-directed learning such as adaptive learning platforms and personalised feedback systems. Moreover, AI-driven learning management systems (LMS) can allow students to set their own learning goals and track progress independently. However, in collectivist cultures like Nigeria, AI should be leveraged to enhance collaboration, such as AI-powered discussion forums, peer feedback systems and cooperative learning systems. Educators should design AI-supported group assignments that encourage collective problem-solving and engagement.

Furthermore, the mediation analysis demonstrates the critical role of instructor support in shaping the AI adoption behaviour of students. This finding demonstrates the importance of instructor support in fostering a positive learning environment and mitigating AI anxiety among students. This aligns with scaffolding principles in educational psychology (Bliss et al., 1996; Umutlu & Gursoy, 2022) which emphasises the need for guided instruction in early AI adoption stages. This means that educators should actively guide students in using AI tools by offering structured training sessions that develop competence in AI-enhanced learning. AI-integrated courses should provide mentorship features where instructors can oversee student interactions with AI and provide timely interventions. In addition, the study demonstrates the need to mitigate AI anxiety and trust-building. The findings show that AI anxiety negatively moderates the relationship between competence, relatedness and AI continuance use intention. This finding aligns with the findings of Budhathoki et al. (2024) that AI anxiety moderates the relationship between competence, relatedness and AI tools continuance use intention.

This finding suggests that students who experience anxiety about using AI could disengage despite having the necessary skills and social support. To address this, HEIs should integrate AI literacy training into their curricula. This can be in the form of awareness campaigns, ethical guidelines and transparency measures to alleviate student concerns and build trust. However, trust did not mediate the relationship between autonomy and AI use. This suggests that ensuring transparency in AI algorithms and decision-making processes can enhance student confidence in using AI tools autonomously. Surprisingly, trust does not moderate the relationship between PC, PR and AI continuance use intention. However, trust moderates the relationship between PA and AI continuance use intention. The findings from this study suggest that the role of trust may be more significant in shaping students' perceptions of autonomy and continuance intention, perhaps due to the risks associated with using and detection of AI tools in educational settings.

This study highlights the significant influence of culture on the acceptability and efficacy of AI technology. The findings underscore the need to consider cultural factors in the design and application of AI systems within educational settings. As demonstrated in this study, the application of AI in pedagogy and learning emphasises the need for teaching methods and approaches that support authentic learning in a variety of contexts. Maintaining student motivation and engagement may be achieved through pedagogical approaches that emphasise student-centred activities and active learning. This study has demonstrated that, in some situations, activities that encourage student autonomy and choice like project-based learning or group projects significantly boost student engagement when using AI technologies. By focusing on pedagogy that considers accessibility, motivation, engagement and support, educators may employ AI to create a more effective and inclusive learning environment for all students. AI tools can offer personalised learning experiences by adjusting to various learning preferences, styles and context. Depending on the context, effective application of AI tools in educational settings can also provide learners who are having real-time difficulties with interactive learning environments, offering practice opportunities, and instant feedback.

5.1. Implications

The study compares AI use in different countries by looking at how likely graduate students are to keep using AI tools. It also builds on Self-Determination Theory (SDT) and Expectation Disconfirmation Theory (EDT) by demonstrating the role of instructors in building trust and reducing anxiety. The study investigates the adoption of AI tools in business education, emphasising the influence of cultural differences on students' motivation and usage of these tools. An interesting conclusion is that the capacity to use these tools is not a strong determinant to keep using them. The research highlights the importance of culturally sensitive AI educational tools and the role of instructor support in shaping students' experiences. The results from this study have significant implications for AI-supported pedagogy and instructional design.

The findings indicate that AI tools should not be deployed as a one-size-fits-all approach. Rather, culturally adaptive AI systems should emphasise personalised learning and autonomy in individualistic cultures; collaborative, community-driven learning in collectivist cultures; and instructor-mediated AI engagement across context to foster trust and reduce anxiety. It is important to develop AI tools with culturally adaptive features to ensure their effectiveness across a diverse learning context. This can help provide equity and access because the use of AI tools can widen the digital divide, as students from certain environments with limited access to digital infrastructure may be disadvantaged.

Additionally, to develop an ethical curriculum that balances privacy, consent, and surveillance, it is crucial to encourage the responsible use of AI. The findings illustrate the essential role of instructors in shaping a generation of learners who are both AI literate and ethically responsible. Furthermore, institutions should provide AI-focused training for instructors to enhance their ability to effectively integrate AI tools in classroom settings. This is because the effectiveness of AI-enhanced pedagogy depends on the preparedness of instructors. Thus, training and resources must be provided to educators to effectively facilitate AI integration. Instructors must signpost students to resources that promote the responsible use of AI because excessive dependence on AI tools for learning can reduce critical thinking and problem-solving skills among students if they are not balanced with traditional pedagogical methods.

Moreover, AI-driven platforms can analyse student learning patterns and provide customised pathways that are tailored to individual progress. This aligns with differentiated instruction theories, which emphasise the need for personalised learning approaches. AI can assist instructors in identifying students who need additional support, thereby promoting an inclusive educational environment that ensures no learner falls behind.

The results also illustrate the importance of balancing AI autonomy and relatedness in different cultural contexts. These findings suggest that when schools use blended learning models, it will be helpful to use AI in ways that allow for flexibility and encourage students to interact with teachers and other students. HEIs might want to come up with hybrid AI-human teaching methods, in which AI provides adaptive content and teachers lead discussions and assessments to foster better learning.

5.2. Conclusions, limitations, and suggestions for future studies

This study examined the factors that influenced the continuance use of AI tools among postgraduate students in Nigeria and the UK by applying SDT and EDT. The study contributes to the literature by investigating how factors such as competence, relatedness, autonomy, instructor support, anxiety, and trust influence continuance usage intentions of students in two countries. This study explores the psychological and emotional aspects of continuous usage of technology in the context of HE. Results suggest that relatedness and autonomy are psychological motivators while trust in AI and anxiety act as emotional boundary conditions that influence the use of AI tools. Moreover, the study found support for the role of instructors in affecting students' motivation to use AI tools. The findings conclude that context is an important aspect of technology adoption and use that cannot be ignored. The results underscore the need of taking cultural factors into account when designing marketing campaigns and implementing AI systems for educational purposes.

The results indicate the need for culturally adaptable strategies and AI systems capable of prioritizing either collaborative or individual characteristics based on the cultural setting. For institutions and policymakers, comprehending these cultural disparities can assist in customizing the use of AI technologies to better align with the motivating consumer expectations from various cultural backgrounds. The results have significant ramifications for the advancement of AI and the formulation of policies on a worldwide level. AI companies must consider cultural disparities while developing and promoting their solutions for various regions, as the motivation for AI adoption differs between cultures. Although these findings provide valuable insights into the utilisation of AI technology in education, it is essential to mention the limitations of the study.

The study's scope was limited to students studying business-related courses in two countries; hence, it may not generalise to students in other programs and in different countries. Thus, there is a need for more research to extrapolate these findings to other cultural contexts. Also, the findings are based on self-reported data of postgraduate students, which may offer some biases that could exclude some long-term changes in continuance use behaviour. Also, the findings have not included the opinions of other relevant stakeholders such as lecturers, policymakers and institutions. Finally, while the SDT and EDT theories offer a robust framework, they may not capture all the factors that influence AI continuance intention. Thus, future studies can expand the contexts to include more countries as well as undergraduate students' perspectives. Also, future research can take a longitudinal approach or use qualitative methodology to understand some of these motivations more in-depth. Other studies can explore additional risks such as ethical use, privacy concerns and how these affect the performance of students. The perspectives of instructors can also be investigated further.

CRediT authorship contribution statement

Egena Ode: Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization. **Rabake Nana:** Writing – review & editing, Writing – original draft, Conceptualization. **Irene O. Boro:** Writing – review & editing, Writing – original draft, Conceptualization. **Darius N. Ikyanyon:** Writing – review & editing, Writing – original draft, Formal analysis.

Data availability

The original data of the study is not publicly available due to ethics restrictions, but it is available from the authors upon reasonable request.

Statement on ethics

The study was approved by an ethical committee with ID: HBSETHICS2223 041. Informed consent was obtained from all participants, and their privacy rights were strictly observed. The data can be obtained by sending request e-mails to the corresponding author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Results of CFA and Model Fit Indices

		United Kingdom			Nigeria		
		Factor Loadings	*CR*	*AVE*	*Factor Loadings*	*CR*	*AVE*
PC1	*I do not feel very competent when I use AI tools in my educational work*	0.71	0.83	0.50	0.59	0.87	0.52
PC2	*My colleagues tell me I am good at using AI tools in my academics*	0.64			0.72		
PC3	*I have been able to learn interesting new skills in AI tools through my academics*	0.83			0.89		
PC4	*Most days I feel a sense of accomplishment from working with AI tools*	0.73			0.84		
PC5	*In my role as a student, I do not get much of a chance to show how capable I am with AI tools*	0.53			0.59		
PC6	*When I am using AI tools, I often do not feel very capable*	0.57			0.65		
PR1	*I really like the people I study with*	0.82	0.94	0.70	0.46	0.90	0.56
PR2	*I get along with people at my university*	0.75			0.73		

(*continued on next page*)

(*continued*)

		United Kingdom			Nigeria		
		Factor Loadings	*CR*	*AVE*	*Factor Loadings*	*CR*	*AVE*
PR3	*I pretty much keep to myself when I am at my university*	0.88			0.79		
PR4	*I consider the people I study with to be my friends*	0.94			0.89		
PR5	*Students at my course care about me*	0.83			0.83		
PR6	*There are not many people at my university that I am close to*	0.83			0.91		
PR7	*The people I study with do not seem to like me much*	0.80			0.50		
PA1	*I feel like I can make a lot of inputs to deciding how I use AI tools in my educational work*	0.40	0.85	0.50	0.51	0.87	0.50
PA2	*I feel pressured at using AI tools in my academics*	0.73			0.70		
PA3	*I am free to express my ideas and opinions on using AI tools in my academics*	0.59			0.65		
PA4	*When I am using AI tools, I have to do what I am told*	0.68			0.78		
PA5	*My feelings toward AI tools are taken into consideration at my university*	0.76			0.73		
PA6	*I feel like I can pretty much use AI tools as I want to at my university*	0.67			0.80		
PA7	*There is not much opportunity for me to decide for myself how to use AI tools in my educational work*	0.83			0.65		
AX1	*I am confident I can learn AI technology-related skills.*	0.52	0.82	0.56	0.54	0.83	0.55
AX2	*I have difficulty understanding most AI technological matters.*	0.56			0.51		
AX3	*I feel apprehensive about using AI technology.*	0.61			0.58		
AX4	*When given the opportunity to use AI technology, I fear I might damage it in some way.*	0.44			0.56		
AX5	*I am sure of my ability to interpret AI technological output.*	0.61			0.67		
AX6	*AI Technological terminology sounds like confusing jargon to me.*	0.50			0.62		
AX7	*I have avoided AI technology because it is unfamiliar to me. .*	0.45			0.60		
AX8	*I am able to keep up with important AI technological advances.*	0.87			0.63		
AX9	*I hesitate to use AI technology for fear of making mistakes I cannot correct.*	0.64			0.66		
TR1	*I trust that AI can offer information and service that's best of my interest.*	0.61	0.72	0.53	0.66	0.71	0.51
TR2	*I trust that my personal data is protected from potential abuse when using AI.*	0.92			0.68		
TR3	*I trust that my privacy is protected when using AI.*	0.50			0.51		
TR4	*I trust that authorities exert effective control over organizations and companies providing AI services.*	0.41			0.59		
IS1	*The instructor played an important role in facilitating ethical use of AI tools*	0.86	0.85	0.56	0.82	0.85	0.54
IS2	*The instructor contributed to AI tools discussions*	0.97			0.89		
IS3	*The instructor was actively helpful when students had problems with AI*	0.83			0.81		
IS4	*I have interacted with the instructor regarding the use of AI tools*	0.40			0.45		
IS5	*The instructor emphasized relationships between AI tools, academic integrity, and possible sanctions*	0.50			0.60		
CI1	*I intend to continue using the AI tools in the future*	0.70	0.71	0.57	0.62	0.70	0.52
CI2	*I will continue using the AI tools in the future*	0.56			0.54		
CI3	*I will keep using the AI tools as regularly as I do now*	0.56			0.56		

CR $\geq$ 0.70 is recommended (Hair, 1997); Fornell and Larcker (1981) recommended a CR value of $\geq$0.60; Fornell and Larcker (1981) recommended an AVE $\geq$0.5.

Appendix 2. Examples of AI tools in used Education

AI Tool	Description	Examples	Research
Natural Language Processing, Chatbots and Virtual Assistants	*Conversational agents that are powered by AI to respond to questions mimicking humans, provide information and help with tasks such as scheduling and resource finding*	ChatGPT, Siri, Bard, Claude, Alexa, Ivy, Ada, Bing	(Budhathoki et al., 2024; Chiu, 2024; Foroughi et al., 2023; Hwang & Chang, 2023; Ilieva et al., 2023; Kooli, 2023; Labadze et al., 2023; Okonkwo & Ade-Ibijola, 2021)
Intelligent Tutoring Systems (ITS)	*Adaptive learning systems that provide bespoke and personalised instruction and feedback based on student knowledge level and learning style*	Cognitive Tutor, ALEKS	(Al-aqbi et al., 2019; Jain & Raghuram, 2024; Lin et al., 2023)
Plagiarism detection	*AI powered algorithm systems that scan content for plagiarism through checkin g a number of databases*	Turnitin, plagiarism.org, QuillBot	(Chaudhry et al., 2023; Michel-Villarreal et al., 2023; Perkins, 2023)
Text rewriting	*Creating content, summarizing and paraphrasing*	Article Forge, QuillBot, Wordtune, Chimp Rewriter, Spinet, WordAI	(Perkins & Roe, 2023; Syahnaz & Fithriani, 2023; Yusuf et al., 2024)
Research Assistants	*help researchers with producing literature reviews, summarizing scholarly articles, and recommending relevant sources or techniques. Semantic.*	Elicit, Consensus, Research Rabbit, Connected papers, Semantic scholar, ResearchAI, Scire, ChatPDF	(Cheah, Lu, & Kim, 2025; Crompton & Burke, 2023; Tahir & Tahir, 2023)
Automated Essay Scoring and Intelligent Grading Assistance	*Grade and evaluate written essays, provide feedback on content, structure and grammar*	Intelligentsia, e-rater, Gradescope	(Crompton & Song, 2021; Ernst, 2019)
Adaptive Learning Platforms	*Use AI to personalise learning experience by adapting learning, pace, and difficulty level based on student performance.*	Smart Sparrow, Knewton	(Cukurova et al., 2023; Tharalson et al., 2023; Tretow-Fish & Khalid, 2023)
Learning Analytics	*Analysing student data such as behaviour, engagement, performance to identify patters and produce insights on how to improve learning outcomes.*	Blackboard Analytics, Canvas Analytics	(Tharalson et al., 2023; Tretow-Fish & Khalid, 2023)
Facial Recognition	*Use facial recognition and biometrics to identity verification and tracking of attendance in hybrid and virtual learning environments.*	Veriff, FaceX	(Akgun & Greenhow, 2022b; 2022a; Li & Zhang, 2023)

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